The Effects of Climate Conditions on Economic Output: Growth versus Level Effects

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Estimating the effects of climate on economic output is crucial for formulating climate policy, but current empirical findings remain ambiguous. We extend the long-difference model to account for time-invariant factors affecting output growth and utilize global subnational data from over 1,600 regions across 196 countries to generate new estimates. We find a significant effect of temperature on output growth in poor regions and a significant effect of precipitation on output growth in rich regions. Given that poor regions are typically hot and that precipitation consistently has a positive effect on rich regions, it is expected that rich regions become richer while poor regions become poorer, leading to a profound climate inequality in the future.
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The impact of climate on economic output—whether it affects the level or growth of output—is widely debated among climate economists (Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015; Tol, 2018; Kalkuhl and Wenz, 2020; Newell, Prest and Sexton, 2021). Some researchers argue that climate only affects output *level* (Kalkuhl and Wenz, 2020; Newell, Prest and Sexton, 2021), with output declining during anomalous climate years but rebounding once the climate returns to prevailing conditions (e.g., the effect of temperature on crop yields). Others contend that climate affects the labor supply (Albert, Bustos and Ponticelli, 2021), capital, and labor productivity (Fankhauser and Tol, 2005; Kjellstrom et al., 2009; Hsiang and Jina, 2014; Graff Zivin, Hsiang and Neidell, 2018; Letta and Tol, 2019; Kahn et al., 2021), thereby having persistent effects on output *growth*. This divergence leads to pronounced differences in the assessment of future climate change damages and the social cost of carbon, resulting in widespread uncertainty about the implementation and effectiveness

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of climate policies(Moore and Diaz, 2015; Tol, 2018; Tsigaris and Wood, 2019).

Early empirical research on the relationship between climate and economic output relied on cross-sectional models (Mendelsohn, Nordhaus and Shaw, 1994; Nordhaus, 2006; Hsiang and Narita, 2012). This approach compares outcomes across cold and hot regions to reveal how currently cool places will change as the climate warms. Although widely used, this approach has been criticized for its vulnerability to omitted variable bias. Any factors correlated with both climate and outcomes but excluded from the model can confound the estimations (Hsiang, 2016; Auffhammer, 2018; Kolstad and Moore, 2020). Given these concerns, later studies employed fixed-effects panel models to explore the relationship between weather and economic outcomes. This approach controls for both unobserved time-invariant and spatial-invariant factors by including individual and time fixed effects, which provides more reliable estimates. Nonetheless, fixed-effects panel models, which use year-to-year variables, actually capture the short-term effects of weather conditions rather than long-term climate impacts (Hsiang, 2016; Auffhammer, 2018; Kolstad and Moore, 2020). Since it is generally difficult for economies to exhibit adaptive behavior in a short period, the estimates derived from annual panel models tend to overstate the projected damages from longer-term climate changes (Burke and Emerick, 2016).

More recent literature adopts the long-difference model, as proposed by Burke and Emerick (2016), which fully accounts for observable adaptation, to provide more plausibly causal estimates of climate damages. This approach estimates the impact by taking the difference in average weather conditions and outcomes over decades. Since the climate is regarded as the probability distribution of weather, average weather conditions are expected to capture the mean level of climate (Hsiang, 2016; Tol, 2019, 2021). The difference between decades is equivalent to the inclusion of individual fixed effects that avoids potential variables that correlate with both climate and outcome. The “long difference” enables capturing the long-term adaptations to the climate. Therefore, the long-difference model overcomes the drawbacks of both cross-sectional and panel models.

However, the standard long-difference model only eliminates the time-invariant factors relevant to the level of output, while time-invariant factors affecting the growth of output remain (we discuss this further in Section I). Additionally, most existing research focuses on national impacts. Damania, Desbureaux and Zaveri (2020) argue that using aggregated data from large spatial scales masks the heterogeneity of weather impacts, leading to insignificant results. This is particularly true for precipitation that its distribution is much more heterogeneous across space compared to temperature (Damania, Desbureaux and Zaveri, 2020). To address this issue, a growing body of literature has started using subnational data for analysis, but the data used has omitted a large number of regions in Africa, Southeast Asia, and Central America (Kalkuhl and Wenz, 2020; Kotz et al., 2021; Kotz, Levermann and Wenz, 2022). These regions are not only hot but also poor. As a result, findings based on inadequate data are expected to underestimate the true impact of climate on economic output (Dong, Tol and Wang, 2023).

To address these challenges, we extend the long-difference model by conducting a second difference to eliminate all possible time-invariant factors. We also use global subnational data with over 1,600 regions from 196 countries to capture nearly all possible climate conditions experienced worldwide. Specifically, we first conduct a panel regression to replicate previous studies and compare our results with those derived from incomplete data. The specification used in this study is consistent with that used by Kalkuhl and Wenz (2020), which identifies the level and growth effects of weather conditions on output separately. Second, we use our extended long-difference model to estimate the long-term effects of climate on economic output. Methodologically this approach extends the standard long-difference model but is also closest to that of Dell, Jones and Olken (2012). Dell, Jones and Olken (2012) uses the summed effect of temperature to distinguish the level and growth effects of temperature on output, whereas we use the summed effect of temperature change. Finally, we incorporate our extended long difference estimates with climate data from 186 global climate emulations to project the percentage change in GDP per capita in 2100 under future 2.0℃ global warming scenarios, providing a potential input to climate policy discussions.

By using the panel model, we first find a significant effect of temperature on output growth. The optimal temperature implied by the model is 15℃. This is two degrees higher than the results of Burke, Hsiang and Miguel (2015). In addition, the effect of temperature is nearly identical in rich and poor regions. 1℃ temperature increase at 26℃ decreases GDP per capita growth by 1.8% in poor regions and 1.7% in rich regions. This result is consistent with prior studies (Burke, Hsiang and Miguel, 2015; Mendelsohn, Dinar and Williams, 2006; Kahn et al., 2021). Poor countries exhibit a larger response mainly because they are hotter on average, not because they are poorer. We also find a consistent positive effect of precipitation on output growth based on the population-weighted regression, suggesting that the majority of people in the world are expected to benefit from an increase in precipitation. Overall, our results support the growth effects of weather conditions on economic output rather than level effects.

The results based on the extended long-difference models further support the growth effects of temperature and precipitation on output. Due to the data limitations, we take the "long difference" between two periods over an average of six years. In this case, our results reflect the medium-term adaptations to the climate but still provide useful insight into long-term climate change adaptation. We find that the cumulative effect of temperature change in poor regions remains consistently negative even after considering more lag effects of climate. However, the cumulative effect of temperature change on rich regions shrinks to zero. These results suggest a significant growth effect of temperature on output in poor regions, but not in rich regions. In contrast, we find that the cumulative effect of precipitation change shrinks to zero in poor regions but remains negative in rich regions. This suggests that precipitation only affects output growth in rich regions, and the marginal effect decreases as precipitation increases. The optimal precipitation implied by the extended long-difference model is 2.2m, which exceeds the annual total precipitation in over 85% of regions in the world, suggesting that the majority of regions benefit from the increase in precipitation. Since both the precipitation and temperature in the vast majority of regions are expected to rise with global climate changes, the results based on the extended long-difference model imply that rich regions are likely to become richer with increased precipitation, while poor tropical regions are expected to become poorer with rising temperatures.

The comparison between the panel and extended long-difference results provides information about the regional adaptation to climate, as the short-term effects are expected to evolve into long-term effects through gradual adaptation over time (Burke and Emerick, 2016). The optimal temperature implied by the extended long-difference model is 21℃, considerably higher than that suggested by the panel model. In addition, we find that the medium-term marginal effect of temperature is considerably different from the short-term effect. 1℃ increase at 10℃ increase output growth in poor regions by 0.69% in the short-term (panel regression results), but it expands to 6.8% in the medium-term (extended long difference results). For hot regions, while the short-term marginal effect of temperature on output growth is significantly negative in poor regions, the medium-term effect is insignificant. These results suggest that climate adaptation not only enhances the positive effect in cold regions but also mitigates the negative effect of temperature in hot regions. Regarding precipitation effects in rich regions, an increase in precipitation shows positive marginal growth effects in most rich regions, although the marginal effects in extremely wet regions show a negative trend, they remain insignificant. In contrast, the short-term effects of precipitation are contently insignificant across all precipitation levels. This suggests that rich regions, except for those that are extremely wet, develop adaptations to take advantage of the increase in precipitation.

The projected percentage changes in GDP per capita vary considerably depending on the statistical approach used. The lowest projection is -1.8% when regional impacts are weighted by the inverse of the number of subnational regions (hereinafter referred to as the number of regions), while the highest projection is 16.9% when weighted by regions' population, and 9.6% when weighted by baseline GDP per capita. The positive projection is because most regions with high populations are projected to benefit from changes in precipitation, such as regions in India, China, and the northeastern United States. Therefore, weighting by population emphasizes the positive effect of precipitation in these regions. In addition, the regions that benefit from changes in precipitation also tend to be rich, therefore, the projected global average change in GDP per capita increased to be positive when weighted by GDP per capita. If we only consider the effect of temperature, the percentage changes in global average GDP per capita are projected to decrease by 19.4%, 16.0%, and 11.8% if weighted by the number of regions, populations, and baseline GDP per capita, respectively. Regions in Africa, Southeast of Asia, and Central America, which are relatively poor and hot, are projected to experience substantial declines in GDP per capita. In contrast, regions in North America and North Europe, which are relatively rich, are projected to see increases in GDP per capita due to rising precipitation. Although precipitation in southern Europe is projected to decrease, the damage from the decrease in precipitation is expected to be offset by the benefits of rising temperatures in these colder regions. Therefore, the gap between rich and poor regions is expected to widen significantly in the future.

Our study makes two key contributions to the rapidly growing literature on climate impacts. First, we extend the standard long-difference model by introducing a second difference, which eliminates time-invariant factors affecting both the level and growth of output, thereby providing more rigorous evidence on the long-term effects of climate on economic output. Second, by using subnational data from nearly all countries, our study offers a comprehensive analysis of the short-term and medium-term effects of temperature and precipitation on economic output, addressing the biases caused by incomplete data. These findings also offer important input for updating damage functions in integrated assessment models used for estimating the social cost of carbon and evaluating climate policies.

The remainder of the paper is organized as follows: Section I develops the extended long-difference model and outlines our empirical approach. Section II introduces the data and provides descriptive statistics. Section III presents our main results based on both the panel and extended long-difference models. Section IV discusses climate adaptation based on these estimates and projects percentage changes in GDP per capita using 186 global climate simulations. Section V concludes the paper.

I. Model and Empirical Approach

A. *Economic Model*

Following Dell, Jones and Olken (2012), we first consider a simple production function to reveal the relationship between weather conditions and output per capita:

$$y_{it} = e^{c_i + \alpha_0 T_{it}^2 + \beta_0 T_{it}} A_{it} \tag{1}$$

where y_{it} is the GDP per capita in region i and year t. c_i captures regional fixed factors that affect the level of output. Following current empirical findings (Burke, Hsiang and Miguel, 2015; Kalkuhl and Wenz, 2020), we consider the non-linear effects of weather conditions T_{it} on GDP per capita. A_{it} measures total factor productivity.

Current literature suggests that weather conditions also affect output *growth*.

Therefore, we have:

$$\Delta ln(A_{it}) = g_i + \gamma_0 T_{it}^2 + \delta_0 T_{it} \tag{2}$$

where g_i captures regional fixed factors that affect productivity growth.

Taking the logarithm of Equation (1) and differencing with respect to time, we derive the growth equation:

$$g_{it} = ln(y_{it}) - ln(y_{it-1}) = \alpha_0 \Delta T_{it} T_{it} + \alpha_0 \Delta T_{it} T_{it-1} + \beta_0 \Delta T_{it} + \Delta ln(A_{it}) \tag{3}$$

Substituting equation (2) into (3) yields:

$$g_{it} = g_i + \alpha_0 \Delta T_{it} T_{it} + \alpha_0 \Delta T_{it} T_{it-1} + \beta_0 \Delta T_{it} + \gamma_0 T_{it}^2 + \delta_0 T_{it} \tag{4}$$

Equation (4) is the panel model used to separately identify the level and growth effects of weather conditions on output, as proposed by Kalkuhl and Wenz (2020). Their estimates are based on data from only 77 countries. We re-estimate this equation using data from 196 countries.

For the derivation of the long-difference model, we first take the average of output per capita and weather conditions over multiple years in Equation (1) to capture the impact of climate. The relationship between the logarithm of average output per capita and climate is then given by:

$$ln(\overline{y_{ip}}) = c_i + \alpha_0 \overline{T_{ip}^2} + \beta_0 \overline{T_{ip}} + ln(\overline{A_{ip}}) \tag{5}$$

For a specific period p, Equation (5) serves as the cross-section model for assessing climate impacts. If uncontrolled, c_i would bias results. To eliminate c_i, we take the difference of Equation (5) over two periods:

$$\begin{aligned} \overline{g_{ip_n}} &= ln(\overline{y_{ip}}) - ln(\overline{y_{ip-n}}) \\ &= (c_i - c_i) + \alpha_0(\overline{T_{ip}^2} - \overline{T_{ip-n}^2}) + \beta_0(\overline{T_{ip}} - \overline{T_{ip-n}}) + (ln(\overline{A_{ip}}) - ln(\overline{A_{ip-n}})) \\ &= \alpha_0 \Delta \overline{T_{ip_n}^2} + \beta_0 \Delta \overline{T_{ip_n}} + \Delta ln(\overline{A_{ip_n}}) \end{aligned} \tag{6}$$

We consider n period differences to capture the long-term effect of climate. g_{ip_n} is the interperiod output growth. Equation (6) is the standard long-difference model, where time-invariant factors relevant to the output level c_i are eliminated through the first difference. However, according to Equation (2), the model may still yield biased estimates as time-invariant factors g_i affecting the productivity interperiod growth $\Delta ln(\overline{A_{ip_n}})$ remain:

$$\begin{aligned} ln(\overline{A_{ip}}) - ln(\overline{A_{ip-n}}) &= \sum_{j=0}^{n-1} \Delta ln(\overline{A_{ip-j}}) \\ &= n g_i + \gamma_0 \overline{T_{ip}^2} + \cdots + \gamma_0 \overline{T_{ip-n+1}^2} + \delta_0 \overline{T_{ip}} + \cdots + \delta_0 \overline{T_{ip-n+1}} \end{aligned} \tag{7}$$

To eliminate g_i, we conduct additional difference of Equation (6) over two periods:

$$
\begin{aligned}
\overline{g_{ip_n}} - \overline{g_{ip_n-n}} = {} & n(g_i - g_i) + \\
& \alpha_0 \Delta \overline{T^2_{ip_n}} - \alpha_0 \Delta \overline{T^2_{ip_n-n}} + \beta_0 \Delta \overline{T_{ip_n}} - \beta_0 \Delta \overline{T_{ip_n-n}} + \\
& \gamma_0 (\overline{T^2_{ip}} - \overline{T^2_{ip-n}}) + \cdots + \gamma_0 (\overline{T^2_{ip-n+1}} - \overline{T^2_{ip-2n+1}}) + \\
& \delta_0 (\overline{T_{ip}} - \overline{T_{ip-n}}) + \cdots + \delta_0 (\overline{T_{ip-n+1}} - \overline{T_{ip-2n+1}})
\end{aligned} \tag{8}
$$

Equation (8) shows that all time-invariant factors (i.e., c_i and g_i) are eliminated after two differences. The estimates based on the equation (8), thus, are more robust than those from the standard long-difference model. Rewriting equation (8) yields:

$$
\begin{aligned}
\Delta \overline{g_{ip_n}} = {} & \overline{g_{ip_n}} - \overline{g_{ip_n-n}} = \\
& (\alpha_0 + \gamma_0) \Delta \overline{T^2_{ip_n}} - \alpha_0 \Delta \overline{T^2_{ip_n-n}} + \gamma_0 \Delta \overline{T^2_{ip_n-1}} + \cdots + \gamma_0 \Delta \overline{T^2_{ip_n-n+1}} + \\
& (\beta_0 + \delta_0) \Delta \overline{T_{ip_n}} - \beta_0 \Delta \overline{T_{ip_n-n}} + \delta_0 \Delta \overline{T_{ip_n-1}} + \cdots + \delta_0 \Delta \overline{T_{ip_n-n+1}} +
\end{aligned} \tag{9}
$$

Where $\Delta \overline{g_{ip_n}}$ and $\Delta \overline{T_{ip_n}}$ are the differences in output growth and average weather, respectively, over n periods. To achieve the "long difference" over two periods, we can increase n or extend the length of p. For example, to obtain a 6-year difference, we can set $n = 2$, the length of $p = 3$ or $n = 3$, the length of $p = 2$ [1]. However, increasing of n leads to more lags in Equation (9). To simplify the regression specification, we consider $n = 2$. In this case, Equation (9) simplifies to:

$$
\begin{aligned}
\Delta \overline{g_{ip}} = \overline{g_{ip}} - \overline{g_{ip-2}} = {} & \\
& (\alpha_0 + \gamma_0) \Delta \overline{T^2_{ip}} + \gamma_0 \Delta \overline{T^2_{ip-1}} - \alpha_0 \Delta \overline{T^2_{ip-2}} + \\
& (\beta_0 + \delta_0) \Delta \overline{T_{ip}} + \delta_0 \Delta \overline{T_{ip-1}} - \beta_0 \Delta \overline{T_{ip-2}}
\end{aligned} \tag{10}
$$

We omit n for clarity. Equation (10) shows that contemporaneous climate change ($\Delta \overline{T^2_{ip}}$ and $\Delta \overline{T_{ip}}$) captures the sum of level and growth effects, while the first and second lags capture the growth effects and the level effects, respectively.

Equations (1) and (2) only consider contemporaneous effects of weather conditions on output and growth. Weather may have lagged effects. A drought, for instance, continues to affect soil moisture and reservoir levels after it ended.

Appendix I generalizes the extended long-difference model based on a general dynamic growth equation with longer lag structures, following the derivation in Dell, Jones and Olken (2012). If we consider l lags of climate effects, the two

[1] Considering the years from 1990 to 1998, if $p = 3$, each period would be 1990-1992, 1993-1995, and 1996-1998. The difference between the two periods, 1996-1998 and 1990-1992, represents a 6-year gap when $n = 2$. Alternatively, if $p = 2$ and $n = 3$, the difference would be between 1990-1991 and 1996-1997, also resulting in a 6-year gap.

period difference of intertemporal output per capita growth is given by:

(11)

$$
\begin{aligned}
\Delta\overline{g_{ip}} =& \overline{g_{ip}} - \overline{g_{ip-2}} = \\
& (\alpha_0+\gamma_0)\Delta\overline{T^2_{ip}} + (\alpha_1+\gamma_0+\gamma_1)\Delta\overline{T^2_{ip-1}} + \cdots + \\
& (\alpha_l+\gamma_{l-1}+\gamma_l-\alpha_{l-2})\Delta\overline{T^2_{ip-l}} + (\gamma_l-\alpha_{l-1})\Delta\overline{T^2_{ip-l-1}} - \alpha_l\Delta\overline{T^2_{ip-l-2}} + \\
& (\beta_0+\delta_0)\Delta\overline{T_{ip}} + (\beta_1+\delta_0+\delta_1)\Delta\overline{T_{ip-1}} + \cdots + \\
& (\beta_l+\delta_{l-1}+\delta_l-\beta_{l-2})\Delta\overline{T_{ip-l}} + (\delta_l-\beta_{l-1})\Delta\overline{T_{ip-l-1}} - \beta_l\Delta\overline{T_{ip-l-2}}
\end{aligned}
$$

where l is the number of lag effects of climate considered. Equation (11) indicates that the second lags capture not only the growth effects but also the lagged level effects. Using Equation (10), therefore, would provide biased estimates or lead to wrong interpretations if there are lagged climate effects.

Equation (11) is our main regression model for analyzing the effects of climate on output. Note that Equation (11) contains $2 \times 2(l+1)$ parameters but has $2 \times (l+3)$ coefficients when we consider l lags of climate effects.

Specifically, there are more estimated coefficients than model parameters for $l < 1$. A linear constraint has to be imposed on the regression. For $l = 1$, the number of coefficients and parameters is the same. For $l > 1$, there are more parameters than coefficients; $l = 2$ is the preferred specification; see below. We are unable to obtain the value of each parameter. However, we can estimate the *cumulative* level and growth effects separately by summing the coefficients. Specifically, The sum of all coefficients of quadratic terms equals $\gamma_0 + \gamma_0 + \gamma_1 + \cdots + \gamma_{l-1} + \gamma_l + \gamma_l = 2(\gamma_0 + \gamma_1 + \cdots + \gamma_l)$, and the sum of all coefficients of linear terms equals $\delta_0 + \delta_0 + \delta_1 + \cdots + \delta_{l-1} + \delta_l + \delta_l = 2(\delta_0 + \delta_1 + \cdots + \delta_l)$. Therefore, these cumulative sums provide insights into the effects of climate:

1) *Primarily Level Effects*: If the accumulated sums of all coefficients for both quadratic and linear terms equal zero, and one of the contemporaneous or lag terms' coefficients is significant, this suggests that the climate effects are primarily level effects without growth effects.

2) *Existence of Growth Effect*: If the accumulated sum of all coefficients for quadratic or linear terms persists, this suggests the existence of a growth effect. Further, if the coefficient of contemporaneous terms ($\Delta\overline{T^2_{ip}}$ and $\Delta\overline{T_{ip}}$) is indistinguishable from the coefficient of first lag terms ($\Delta\overline{T^2_{ip-1}}$ and $\Delta\overline{T_{ip-1}}$), and the half of summed coefficients is also indistinguishable from them, this suggests contemporaneous growth effect only.

3) *Combination of Lagged Growth and Level Effects*: Other scenarios would suggest a combination of lagged growth and level effects.

B. Empirical Model

A potential drawback of the cross-sectional long-difference model is that estimates may be biased if within-country, time-varying factors are correlated with both climate and output (Burke and Emerick, 2016). To address this concern, we construct a panel of extended long-differences that include several periods for the variables of interest. Building on equation (11), we consider the following specification for regression:

$$\Delta g_{ip} = \sum_{j=0}^{l+2} \rho_j \mathbf{\Delta T^2_{ip-j}} + \sum_{j=0}^{l+2} \sigma_j \mathbf{\Delta T_{ip-j}} + \eta_i + \theta_p + \epsilon_{ip} \tag{12}$$

Where Δg_{ip} is the difference between the interperiod output per capita growth in region i and period p and that from two periods ago. We first calculate the three-year average of output per capita and take the logarithm to obtain $ln(\overline{y_{ip}})$. Then we take the difference of $ln(\overline{y_{ip}})$ between period p and the value from two periods ago $p-2$ to get the interperiod output growth g_{ip}. Finally, we calculate the second difference of the interperiod output growth g_{ip} between period p and period $p-2$ to get the Δg_{ip}[2]. Although data limitations prevent us from averaging variables over more extended periods, the three-year averages and two-period differences (resulting in six-year gaps with nine years considered) still enable us to capture the medium-term effects of climate change over nearly a decade. l represents the number of lag effects of climate considered.

$\mathbf{T_{i,p}} = (T_{ip}, P_{i,p})$ is a vector of average annual mean temperature (in ℃) and average annual total precipitation (in m) over three years. $\mathbf{\Delta T_{ip}}$ is the difference between average temperature and precipitation between period p and period $p-2$. η_i is the region fixed effect, which controls for any unobserved subnational level effects. θ_p is the period fixed effect to control unobserved, spatially invariant factors, such as the El Niño or La Niña events. ϵ_{ip} is the error term clustered at the country level as suggested by Cameron and Miller (2015) and MacKinnon, Nielsen and Webb (2023). This clustering level is also consistent with the approach used by Kalkuhl and Wenz (2020).

Given that we are estimating non-linear models, we also calculate the marginal effects of Equation (12) at each point of $\mathbf{T_{i,p}}$ to determine the climate growth effects. In particular, considering the model without lagged growth effects in equation (10) for instance, the marginal effect on output growth at a specific average climate condition $\mathbf{T}^*$ is $\hat{\tau} = (\hat{\rho_0} + \hat{\rho_1} + \hat{\rho_2})\mathbf{T}^* + (\hat{\sigma_0} + \hat{\sigma_1} + \hat{\sigma_2})/2$. The advantage of this approach is that it avoids separately summing up the linear

[2]Specifically, we compute average output for the years 1990-1991, 1992-1994, 1995-1997, ..., and 2013-2015, and take logarithm of them (While only first period contains two years, all others contains three years). We then calculate the first difference by subtracting the logarithm of average output between 1990-1991 and 1995-1997 (label it $p1$), 1992-1994 and 1998-2000 (label it $p2$), ..., and 2007-2009 and 2013-2015 (labe it $p7$) to get the interperiod output growth. We finally calculate the second difference by subtracting the interperiod output growth between $p1$ and $p3$, $p2$ and $p4$,..., and $p5$ and $p7$.

and quadratic terms to identify the climate effects. Note that if the lagged effects exist, $\hat{\tau}$ captures the cumulative marginal effects over periods when temperature is unchanged[3].

Due to varying definitions of subnational regions across countries, some countries have more granular subnational divisions, while others have coarser ones. For instance, Brazil and Italy have the same number of subnational regions, but Brazil's area is 28 times that of Italy. Using subnational data directly, therefore, emphasizes the climate change responses of countries with more subnational divisions. To address this issue, we employ two strategies: First, we use the inverse of the number of subnational regions in a country as a weight in the regression (hereinafter referred to as region weighting). The interpretation of these results reflects the effects of climate on a country's average economic output, which allows us to compare our results with those from other studies based on country-level data. Second, we use the population of subnational regions as a weight in the regression(hereinafter referred to as population weighting). The interpretation of these results reflects the effect of climate on a person's average economic output (income). These strategies ensure that our findings are robust and comparable across different contexts.

II. Data and Descriptive Statistics

A. Data

The temperature and precipitation data for this study are derived from the CRU database (https://crudata.uea.ac.uk/cru/data/hrg/). This database provides a global high-resolution (0.5°×0.5°resolution) monthly grid of land-based observations dating back to 1901. The data is developed based on station observations, with the grid data obtained using angular-distance weighting interpolation. This CRU database also implements a degree of homogenization and shows no substantial discrepancies with other climate databases. It is widely used in the literature (Kalkuhl and Wenz, 2020; Song, Wang and Zhao, 2023; Malpede and Percoco, 2024), allowing for the comparison of our results with findings from other studies.

To process the data, We first determine whether a grid's centroid falls within a region's boundaries. The monthly grid data is then aggregated to the subnational level using area weights to obtain regions' monthly average temperature and monthly total precipitation. These monthly observations are finally aggregated by averaging (for temperature) or summing (for precipitation) to obtain

[3]If we consider two lags effects ($l = 2$), the marginal growth effect is $\tau = 2 \times \gamma_0 T_{ip} + 2 \times \gamma_1 T_{ip-1} + 2 \times \gamma_2 T_{ip-2} + \delta_0 + \delta_1 + \delta_2$. Since there are more parameters than coefficients, we are unable to obtain the specific value of each parameter. However, the sum of parameters can be obtained by summing the coefficients in equation (12), i.e.$\gamma_0 + \gamma_1 + \gamma_2 = (\hat{\rho_0} + \hat{\rho_1} + \hat{\rho_2} + \hat{\rho_3} + +\hat{\rho_4})/2$; $\delta_0 + \delta_1 + \delta_2 = (\hat{\sigma_0} + \hat{\sigma_1} + \hat{\sigma_2} + \hat{\sigma_3} + +\hat{\sigma_4})/2$. If temperature is unchanged, i.e. $T_{ip} = T_{ip-1} = T_{ip-2} = T_i$, the marginal growth effect $\tau = 2 \times (\gamma_0 + \gamma_1 + \gamma_2) \times T_i + \delta_0 + \delta_1 + \delta_2$. Therefore, the marginal effect $\hat{\tau}$ at a specific average climate conditions $\mathbf{T}^*$ can be estimated by $\hat{\tau} = (\hat{\rho_0} + \hat{\rho_1} + \hat{\rho_2} + \hat{\rho_3} + +\hat{\rho_4})\mathbf{T}^* + (\hat{\sigma_0} + \hat{\sigma_1} + \hat{\sigma_2} + \hat{\sigma_3} + \hat{\sigma_4})/2$.

the annual mean temperature and annual total precipitation values.

Gross domestic product per capita (2011 PPP) data is obtained from Kummu, Taka and Guillaume (2018). The database was initially collected by Gennaioli et al. (2013) based on various government statistical agencies. It includes GDP data for 1569 subnational regions across 110 countries between 1990 and 2010, covering most countries in Central and South Africa - regions that are poorly covered by other subnational GDP databases. Kummu, Taka and Guillaume (2018) extended the time series of this database from 2010 to 2015 and filled in missing countries based on national GDP data. Overall, the database developed by Kummu, Taka and Guillaume (2018) covers global subnational GDP data from 1990 to 2015 with no missing areas.

The population data used for weighting is derived from Liu et al. (2024), who developed the first available annual continuous global gridded population database from 1990 to 2020 using a data fusion framework based on five widely used population data products. To obtain the regions' population, we first determine the grid's centroid, and then sum up the gridded data into the subnational level if the grid's centroid falls within a region.

B. *Descriptive Statistics*

Table 1 summarizes the subnational data used in this study. Our sample includes 1,666 regions from 196 countries, covering almost all countries and populations globally. The global average GDP per capita from 1990 to 2015 is \$11315. This is roughly equivalent to the average GDP per capita of Algeria and Thailand. Qatar has the highest average GDP per capita (\$104,617 per person per year), while Somalia has the lowest (\$607/p/yr). The global average subnational temperature is 18.6℃ if weighted by regions, while the population-weighted temperature is 19.0℃. This slight increase in population-weighted temperature indicates that people tend to live in warmer regions. People also tend to live in wetter regions, but the difference between average region-weighted precipitation (1.12m) and average population-weighted precipitation (1.11m) is relatively small.

Figure 1 shows the average temperature (Panel A), precipitation (Panel B), GDP per capita (Panel C), and GDP per capita growth rate (Panel D) over time. All these variables exhibit increasing trends starting from 1990. On average, the global temperature increased by 0.50℃, precipitation increased by 46 mm, GDP per capita increased by \$6168, and the GDP per capita growth rate increased by 2.7% when comparing the average values from 1990-1994 to those from 2011-2015.

These increasing trends indicate an underlying non-stationary process, which may result in spurious results when using cross-sectional or panel models. However, by taking the first difference of temperature and precipitation and the second difference of GDP per capita—the variables used in our main regression, all of them show a stationary process in figure trends (Figure A1). Appendix II provides more robust unit root tests, which confirm that all variables in the main regression models are stationary.

Table 1—Summary statistic

Variable		Mean	SD	Min	Max	Obs.	Regions	Countries	Year
GDP per capita (region-weighted)	y_{it}	14857	19081	177	459271.4	43316	1666	196	1990-2015
GDP per capita (population-weighted)	y_{it}	11315	14141						
Annual mean temperature() (region-weighted)	T_{it}	18.64	8.14	-19.76	29.71				
Annual mean temperature(°C) (population-weighted)	T_{it}	18.96	7.39						
Annual total precipitation(m) (region-weighted)	P_{it}	1.12	0.77	0.00027	6.31				
Annual total precipitation(m) (population-weighted)	P_{it}	1.11	0.66						

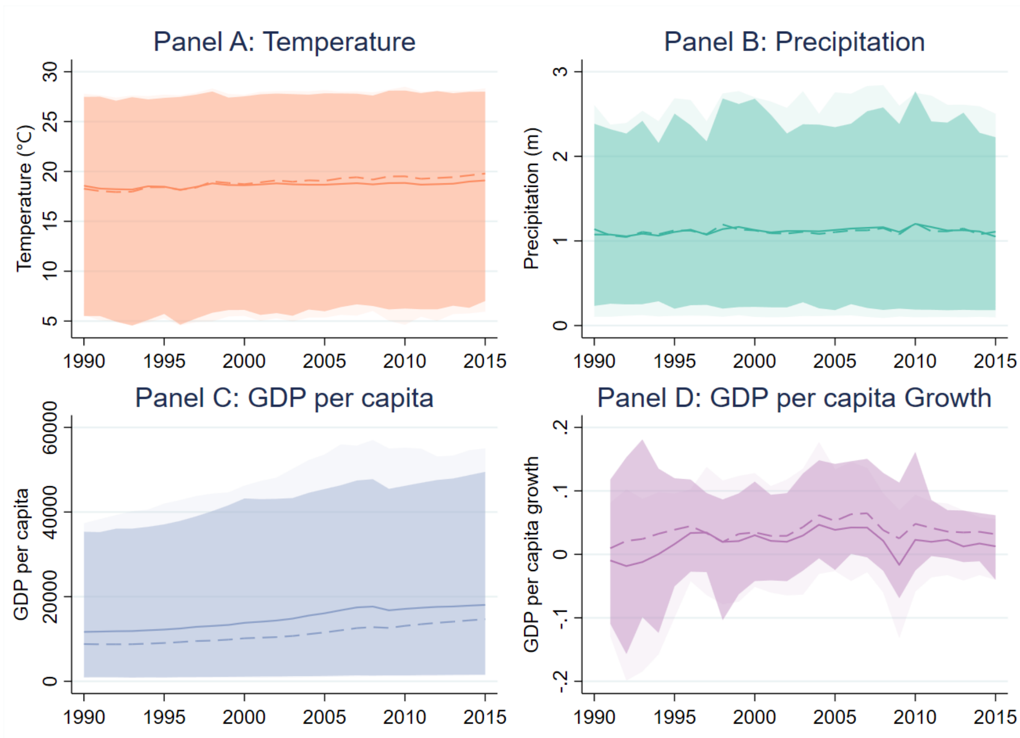

Figure 1. Changes in temperature, precipitation, and GDP per capita from 1990 to 2015.

Note: Figure 1 shows the global average temperature, precipitation, GDP per capita, and GDP per capita growth from 1990 to 2015. The solid lines represent the region-weighted average data. The dash lines represent the pop-weighted average data. Dark shadows represent the fifth to ninety-fifth percentile of region-weighted data. Light shadows represent the fifth to ninety-fifth percentile of pop-weighted data.

III. Empirical results

A. Replication and extension of Kalkuhl and Wenz

We first conduct a panel regression to assess the short-term effects of weather conditions on output. These results allow us to identify the degree of adaptation to long-term climate change by comparing them with the extended long-difference results. The panel model is developed based on Equation (4). We ignore the lag term of $\alpha_0 \Delta T_{it} T_{it-1}$ to provide a parsimonious model, which still allows us to capture the level and growth effects of weather conditions separately. The specific regression model is as follows:

$$g_{it} = \alpha_0 \mathbf{\Delta T_{it} T_{it}} + \beta_0 \mathbf{\Delta T_{it}} + \gamma_0 \mathbf{T_{it}^2} + \delta_0 \mathbf{T_{it}} + \eta_i + \theta_t + h_i(t) + \epsilon_{it} \tag{13}$$

Where Δg_{it} is the annual GDP per capita growth in region i and year t. $\mathbf{T_{i,t}}$ = $(T_{it}, P_{i,t})$ is a vector of annual mean temperature (in ℃) and annual total precipitation (in m). η_i and θ_t are the country fixed effect and year fixed effect. We also consider the quadratic region-specific time trends fixed effect $h_i(t) = \lambda_{i1}^2 + \lambda_{i2}$ to control gradual changes in individual regions' growth rates driven by slowly changing factors.

The results of the panel regression are presented in Table 2. Columns (1) and (2) show the results based on region-weighted data, whereas columns (3) and (4) are based on population-weighted data. Columns (1) and (3) provide the results based on the model developed by Burke, Hsiang and Miguel (2015), which only includes the quadratic function to analyze the aggregate effects (sum of both level and growth effects) of weather conditions. Column (1) shows a significant effect of temperature on GDP per capita, while the effect of precipitation is insignificant. These results are consistent with Burke, Hsiang and Miguel (2015). However, when we use the population-weighted data for the regression, we find a significant effect of precipitation, while the significance of the temperature effect becomes weaker. The optimal precipitation implied by column (3) is 2.1 m, which is higher than 90% regions' precipitation, suggesting a consistently positive effect of precipitation for most people.

The difference between the results in columns (1) and (3) may be due to the fact that population-weighted results emphasize the responses of regions with higher populations. In populous regions, where domestic and industrial water demand is heightened, development is primarily hindered by precipitation. Therefore, an increase in precipitation consistently has a positive effect in these regions. In contrast, regions with lower populations have lower water demand, thus, changes in precipitation have a limited impact on their output. However, for the effect of temperature, higher population density enables them to better cope with temperature changes (e.g. cities have more air conditioning than rural areas). Therefore, the effect of temperature in column (3) is less significant than in column (1).

Columns (2) and (4) represent the results based on Equation 13, which estimates the level and growth effects of weather conditions separately. We find a significant effect of temperature on output growth, while its effect on output level is insignificant when using region-weighted regression (column (2)). These results suggest that the temperature effect identified in column (1) is primarily due to its effect on output growth. The optimal temperature implied by column (2) is 14.5℃, lower than the 15.8℃ implied by column (1). This may be due to the positive trend of temperature on the level of output that increases the aggregate optimal temperature, as the coefficient of $\Delta T \cdot T$ in column (2) is positive. In this case, the model developed by Burke, Hsiang and Miguel (2015) may underestimate the effect of temperature on output growth. Column (4) also shows a significant effect of temperature on output growth. The optimal temperature implied by column (4) is 12℃, which is substantially lower than that implied by column (2), but its magnitude and significance are weaker. Overall, all of these specifications suggest a low optimal temperature level, which the current global average temperature has already surpassed, implying that further global warming could substantially reduce the short-term growth of global GDP per capita.

Looking for the precipitation, the effect of precipitation on output growth in columns (2) and (4) are both insignificant, but we find a significant effect of precipitation on the level of output in column (4). This, to some extent, explains the significant effect of precipitation in column (3). In other words, the precipitation effect identified in column (3) is due to its effect on the output level. However, the statistical significance is also weak. Given the potential heterogeneity of precipitation effects at different levels, further analysis of marginal effects at different precipitation conditions is needed.

Figure 2 shows the marginal effects of temperature and precipitation on output growth from columns (2) and (4) in Table 2. Table 3 further presents the marginal effects of temperature and precipitation at the 25%, mean, and 75% subpoint values. Panel A and Panel B show the marginal effects of temperature on output. We find that the marginal level effects of temperature are consistently insignificant in both region- and population-weighted regressions. The marginal effects of temperature on output growth are also insignificant if weighted by population. However, we find significant marginal growth effects of temperature when weighted by regions. 1 ℃ increase in temperature is expected to increase GDP per capita growth by 1.5% in regions with an average temperature of 5℃ and reduce GDP per capita growth by 1.8% at 26℃.

Regarding the marginal effects of precipitation, Panel C and Panel D show that the marginal effects of precipitation on both level and growth of output are consistently insignificant across all precipitation levels if weighted by the number of regions. However, if we weighted by population, an increase in precipitation shows a significant negative marginal effect on output level in extremely wet regions. 100 mm increase in precipitation decreases GDP per capita growth by 0.1% in regions with an annual total precipitation of 2.2m (90% percentile in our sample). In addition, we find that the effect of precipitation on output growth is consistently significant and positive if weighted by population. 100 mm increase in precipitation consistently increases GDP per capita growth by 0.1% at each precipitation level. This result suggests that although wet regions with large populations are vulnerable to short-term changes in precipitation, they have adequate capacity to adapt to these changes, leading to long-term increases in output growth. Note that changes in precipitation are quite heterogeneous across the world. While

Table 2—Panel regression results

	(1)	(2)	(3)	(4)
Dep. var.	Annual GDP per capita growth			
ΔT		-0.00588		-0.000756
		(0.0047)		(0.0030)
$\Delta T \cdot T$		0.000507		0.000211
		(0.0003)		(0.0002)
ΔP		-0.00288		0.0174
		(0.0096)		(0.0128)
$\Delta P \cdot P$		-0.000998		-0.0126**
		(0.0040)		(0.0059)
T	0.0175***	0.0226**	0.00533*	0.00563
	(0.0067)	(0.0096)	(0.0031)	(0.0038)
T^2	-0.000554***	-0.000774***	-0.000149*	-0.000233**
	(0.0002)	(0.0003)	(0.0000)	(0.0001)
P	0.0134	0.0169	0.0324**	0.0118
	(0.0096)	(0.0148)	(0.0145)	(0.0113)
P^2	-0.00448*	-0.00405	-0.00796**	-0.000316
	(0.0025)	(0.0036)	(0.0031)	(0.0027)
Obs.	41650	41650	41650	41650
R^2	0.214	0.215	0.327	0.328
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region-specific time trend FE	Yes	Yes	Yes	Yes
Weight	Region	Region	Pop.	Pop.

Note: Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

North Africa, the Middle East, and Central Asia are expected to experience an increase in precipitation, Southern Europe, Central America, and Southeast Asia will experience a decrease in precipitation (IPCC et al., 2021). In this case, the decrease in precipitation in these regions is expected to decrease their GDP per capita growth.

B. *Difference in long differences*

Table 4 presents the cumulative effects based on the extended long-difference model in Equation (12), considering no lags, one lag, and two lags of climate effects on output. Columns (1) to (3) are the estimates weighted by region, whereas columns (4) to (6) are weighted by population. Appendix IV provides complete

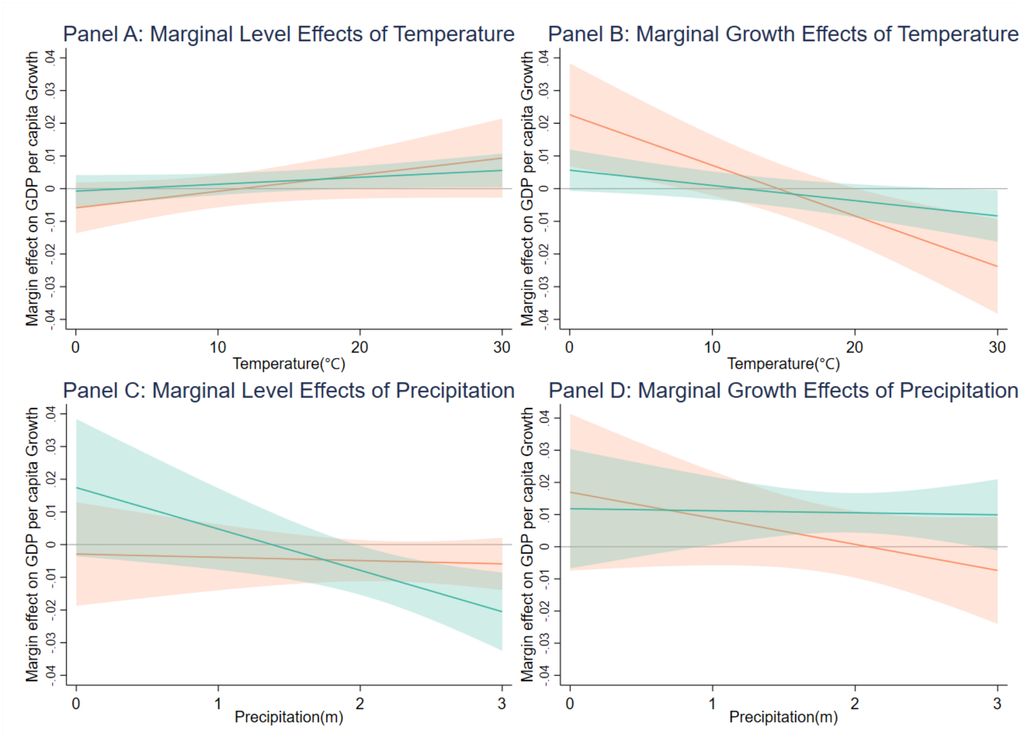

Figure 2. Marginal effects of temperature, precipitation on output

Note: Figure 2 shows the marginal effects of temperature on GDP per capita growth (top), and the marginal effects of precipitation on GDP per capita growth (bottom). The orange line represents the estimates based on region-weighted regression. The green line represents the estimates based on population-weighted regression. The shadow areas represent the 90% confidence interval.

regression results with all lag terms. Comparing results from specifications, considering more lag effects of climate substantially increases the R^2, especially in the two-lag model, where R^2 increases from 0.341 to 0.499, and 0.410 to 0.583 compared to the one-lag model[4]. In addition, some of the cumulative effects change across specifications, suggesting the existence of lag effects of climate. Therefore, we consider the two-lag models in columns (3) and (6) as our preferred models. However, the uncertainty in the cumulative effect also increases with more lags being included as additional uncertain parameters are added. Therefore, compared to the statistical significance of cumulative effects, we prefer to focus on the changes of cumulative effects. If the cumulative effects are stable across models, this indicates the presence of growth effects. If the cumulative effects eventually shrink to 0, and one of the regression variables is significant, this indicates the

[4]The R^2-adjusted for no-lags, one-lag and two-lags models are 0.080, 0.117, 0.244 for region-weighted regression, and they are 0.120, 0.210, 0.371 for population-weighted regression.

Table 3—Marginal effects of Panel regression results

	(1)	(2)	(3)	(4)	(5)	(6)
		Level effect			Growth effect	
Panel A: Area-weighted Panel data						
Temperature	11℃	19℃	26℃	11℃	19℃	26℃
	-0.000301	0.00376	0.00730	0.00558	-0.00680	-0.0176**
	(0.0030)	(0.0042)	(0.0061)	(0.0053)	(0.0049)	(0.0071)
Precipitation	0.5m	1.1m	1.6m	0.5m	1.1m	1.6m
	-0.00338	-0.00398	-0.00448	0.0129	0.00803	0.00397
	(0.0078)	(0.0058)	(0.0045)	(0.012)	(0.0084)	(0.0066)
Panel B: Population-weighted Panel data						
Temperature	13℃	19℃	26℃	13℃	19℃	26℃
	0.00199	0.00325	0.00473*	-0.000424	-0.00322	-0.00648
	(0.0019)	(0.0020)	(0.0026)	(0.0025)	(0.0030)	(0.0040)
Precipitation	0.6m	1.1m	1.5m	0.6m	1.1m	1.5m
	0.00985	0.00352	-0.00154	0.0114	0.0111*	0.0109***
	(0.0096)	(0.0071)	(0.0055)	(0.0083)	(0.0060)	(0.0045)

Note: Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

significant level effects.

As columns (1) to (3) show, the summed coefficients of temperature remain fairly stable as more lags are considered. This result, therefore, suggests a growth effect of climate on output. The optimal temperature implied by column (3) is roughly 19℃, substantially higher than that implied by panel regression. In contrast, the cumulative effects of temperature in columns (4) to (6), which are weighted by population, show decreasing trends, and the magnitude of the summed coefficient of ΔT^2 in column (6) is almost equal to zero. This suggests the limited effect of temperature on output growth in large population regions, consistent with findings from the panel regression.

Looking for the precipitation effects, the cumulative effect of precipitation on output growth increases as more lag effects are considered (columns (1) to (3)). This suggests: 1) the existence of lag effects of precipitation on output growth, the summed coefficients are creased with more lagged growth effects considered. or 2) the combination of growth and level effects, but their effects are opposite (the growth effect is negative, while the level effect is positive). The summed coefficients is increase by diminish the level effects[5]. No matter which possibilities, columns (1) to (3) suggest the existence of the growth effect of precipitation. For

[5]Recalling equation (11), if we consider two lag effects of climate on output, the equation (11) simplifies to: $\Delta\overline{g_{ip}} = (\alpha_0+\gamma_0)\Delta\overline{T^2ip} + (\alpha 1+\gamma_0+\gamma_1)\Delta\overline{T^2ip-1} + (\alpha 2+\gamma_1+\gamma_2-\alpha_0)\Delta\overline{T^2ip-2} + (\gamma 2-\alpha_1)\Delta\overline{T^2ip-3} - \alpha 2\Delta\overline{T^2ip-4} + (\beta 0+\delta_0)\Delta\overline{T_{ip}} + (\beta_1+\delta_0+\delta_1)\Delta\overline{T_{ip-1}} + (\beta_2+\delta_1+\delta_2-\beta_0)\Delta\overline{T_{ip-2}} + (\delta_2-\beta_1)\Delta\overline{T_{ip-3}} - \beta_2\Delta\overline{T_{ip-4}}$. The sum of coefficients of the first three quadratic terms is: $2(\gamma_0+\gamma_1)+\gamma_2+\alpha 1+\alpha 2$. Therefore, the estimates of cumulative effect are biased by the lagged level effects.

the cumulative effect of precipitation based on population weighting, although the cumulative effect increases from columns (4) to (5), it finally decreases in column (6). In addition, the absolute value of the summed coefficient of ΔT^2 in column (6) is also lower than that in column (3). This suggests that even though there is a growth effect, the effect is smaller in large population regions.

Overall, the results in Table 4 suggest a potential growth effect of temperature and precipitation when weighted by the number of regions. In contrast, both cumulative effects of temperature and precipitation decrease with more lag effects considered when weighted by the population, implying that larger population regions have higher adaptation to medium-term climate change. However, all of the statistical significance of these effects is weak. This could be due to the increased uncertainty of including too many lag variables, but it may also stem from the heterogeneous adaptation between rich and poor regions, as suggested by previous studies. To explore this, we conduct a heterogeneity analysis in the next section.

C. Heterogeneity

To examine the differential impacts of climate on output in rich versus poor regions, we first calculate each region's average GDP per capita over periods and divide them to be "rich" and "poor" based on region- or population-weighted median value. Regions with average GDP per capita above the median are classified as "rich," while those below are classified as "poor." We then interact temperature and precipitation with a dummy variable indicating whether a region is poor in the two-lags model[6]. Table 5 (Temperature effects) and Table 6 (Precipitation effects) summarize the cumulative effects of climate on output weighted by region(column (1) to (3)) and weighted by population (column (4) to (6)) across poor and rich regions. Appendix IV provides complete regression results with all variables.

Columns (1) to (3) in Table 5 show that the summed coefficients of temperature in poor regions remain stable and significant, providing rigorous evidence of the growth effects of temperature in poor regions. The optimal temperature implied by column (3) is 19℃. In contrast, the cumulative effect of temperature in rich regions continues to decrease as more lag effects are considered and the summed coefficient of ΔT^2 in column (3) is also close to zero. In addition, all the coefficients for rich regions are insignificant (Column (3) in Table A4). These results suggest that there is no effect of temperature on rich regions' output, implying people in rich regions have higher adaptability to medium-change temperature change compared to the poor regions.

[6]The dummy variable equals 0 for poor regions and 1 for rich regions. The coefficients of the quadratic and linear terms for temperature or precipitation capture the nonlinear effect of climate on output in poor regions, while the interaction terms capture the difference between poor and rich regions. The nonlinear effect of climate on output in rich regions is therefore calculated by summing the coefficients of the quadratic and linear terms with the coefficients of the interaction terms.

TABLE 4—EXTEND LONG DIFFERENCE RESULTS

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
ΔT^2	-0.00495***	-0.00503**	-0.00535**	-0.00295***	-0.00325**	-0.00364***
	(0.0013)	(0.0021)	(0.0024)	(0.0009)	(0.0015)	(0.0009)
$L1:\Delta T^2$	-0.00629***	-0.00423***	-0.00237	-0.00306**	-0.00158*	-0.000437
	(0.0015)	(0.0016)	(0.0020)	(0.0012)	(0.0009)	(0.0013)
ΔT	0.186***	0.126*	0.175*	0.0867**	0.0482	0.0877***
	(0.0447)	(0.0740)	(0.0946)	(0.0354)	(0.0609)	(0.0395)
$L1:\Delta T$	0.240***	0.101*	0.0138	0.0802*	0.0198	0.0190
	(0.0631)	(0.0522)	(0.0615)	(0.0476)	(0.0521)	(0.0631)
Sum of all coeff. of ΔT^2	-0.0126***	-0.0157***	-0.0137*	-0.00612**	-0.00446	-0.000161
	(0.00293)	(0.00553)	(0.00821)	(0.00245)	(0.00365)	(0.0052)
Sum of all coeff. of ΔT	0.479***	0.443**	0.525	0.160*	0.0302	0.0603
	(0.126)	(0.204)	(0.343)	(0.095)	(0.137)	(0.177)
ΔP^2	-0.0238	-0.115**	-0.106**	-0.0558*	-0.145***	-0.0978**
	(0.0289)	(0.0565)	(0.0433)	(0.0325)	(0.0412)	(0.0424)
$L1:\Delta P^2$	-0.0442	-0.0851	-0.126*	-0.0741	-0.0911**	-0.0755
	(0.0370)	(0.0567)	(0.0694)	(0.0537)	(0.0379)	(0.0539)
ΔP	0.0897	0.356	0.371*	0.221*	0.558***	0.358**
	(0.148)	(0.264)	(0.197)	(0.131)	(0.141)	(0.150)
$L1:\Delta P$	0.128	0.212	0.469	0.228	0.244*	0.256
	(0.173)	(0.248)	(0.286)	(0.159)	(0.138)	(0.182)
Sum of all coeff. of ΔP^2	-0.088	-0.335*	-0.382	-0.148	-0.390***	-0.104
	(0.074)	(0.176)	(0.240)	(0.107)	(0.139)	(0.228)
Sum of all coeff. of ΔP	0.256	0.806	1.26	0.456	1.14**	0.318
	(0.346)	(0.782)	(0.970)	(0.318)	(0.461)	(0.728)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.266	0.341	0.499	0.297	0.410	0.583
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Table A3 provides complete regression results with all lags. Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

For the effects weighted by population, we find that the cumulative effect in columns (4) to (6) shows an increasing trend for poor regions. The statistical significance of this cumulative effect also increases. Furthermore, the cumulative effect in column (6) is almost the same as that in column (3). This suggests an equivalent effect of temperature on both densely and sparsely populated regions. For the effects of precipitation, we find a positive growth effect of temperature for rich regions. The summed coefficient of quadratic terms in columns (4) to (6) keeps increasing, and its statistical significance also increases. This indicates that the increase in the temperature benefits the output in rich regions with large populations.

Table 5—Extended long difference results between poor and rich regions

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
$\Delta T^2 \times poor$	-0.00859***	-0.00562*	-0.00648**	-0.00155	-0.00141	-0.00558*
	(0.0032)	(0.0034)	(0.0026)	(0.0024)	(0.0028)	(0.0032)
$L1 : \Delta T^2 \times poor$	-0.0100***	-0.00715***	-0.00290	-0.00536***	-0.00356**	-0.00117
	(0.0038)	(0.0023)	(0.0027)	(0.0020)	(0.0017)	(0.0030)
$\Delta T \times poor$	0.345***	0.165	0.242**	-0.0325	-0.102	0.0900
	(0.1322)	(0.1347)	(0.0935)	(0.1330)	(0.1248)	(0.1387)
$L1 : \Delta T \times poor$	0.341**	0.145**	-0.00132	0.156**	0.103	0.0000209
	(0.1364)	(0.0666)	(0.0741)	(0.0733)	(0.0708)	(0.1309)
Sum of coeff. of ΔT^2 in poor	-0.0223***	-0.0234***	-0.0231***	-0.00768*	-0.00705	-0.0235**
	(0.00483)	(0.00752)	(0.00889)	(0.0045)	(0.00571)	(0.0115)
Sum of coeff. of ΔT in poor	0.835***	0.669**	0.896***	0.127	0.234	1.08**
	(0.202)	(0.281)	(0.313)	(0.21)	(0.214)	(0.421)
$\Delta T^2 \times rich$	-0.00569**	-0.00357	-0.00474	0.00225	0.000917	0.00291
	(0.0022)	(0.0024)	(0.0037)	(0.0015)	(0.0023)	(0.0021)
$L1 : \Delta T^2 \times rich$	-0.00291*	-0.00154	-0.000145	-0.00199**	0.000126	0.00174
	(0.0018)	(0.0025)	(0.0033)	(0.0010)	(0.0014)	(0.0024)
$\Delta T \times rich$	0.181***	0.0902	0.137	-0.0504	-0.0159	-0.0345
	(0.0608)	(0.0737)	(0.1127)	(0.0541)	(0.0772)	(0.0688)
$L1 : \Delta T \times rich$	0.129*	0.0482	-0.0139	0.0739**	-0.0380	-0.0606
	(0.0689)	(0.0693)	(0.0891)	(0.0361)	(0.0476)	(0.0669)
Sum of coeff. of ΔT^2 in rich	-0.0104**	-0.00866	-0.00435	0.00232	0.000504	0.0177**
	(0.00409)	(0.00691)	(0.0127)	(0.0027)	(0.00628)	(0.00731)
Sum of coeff. of ΔT in rich	0.360**	0.254	0.276	-0.0647	-0.109	-0.422**
	(0.156)	(0.224)	(0.46)	(0.114)	(0.176)	(0.212)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.276	0.352	0.511	0.319	0.429	0.611
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Table A4 provides complete regression results with all lags.Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

Table 6 presents the effects of precipitation on output. Columns (1) to (3) show that the cumulative effect of precipitation decreases and the summed coefficient of ΔP^2 approaches zero for poor regions. The contemporaneous and lag terms of precipitation are also insignificant across models. These results suggest there is a lack of significant effects of precipitation on both the level and growth of output in poor regions. In contrast, we find an increasing trend in the cumulative effect for rich regions, with their statistical significance also increasing. This suggests a growth effect of precipitation in rich regions. The optimal precipitation suggested in column (3) is 2.1 m, which is higher than the annual total precipitation in most regions. This result suggests a positive effect of precipitation on output growth in most regions, although the marginal benefit decreases.

Looking at the effect of precipitation on output weighted by population in columns (4) to (6), the cumulative effect of precipitation for poor regions remains stable across models, but the statistical significance is weak. For the effects of precipitation in rich regions, both the magnitude and statistical significance decrease as more lag effects are considered, suggesting there is no growth effect of precipitation in rich regions with large populations. However, we find a significant negative level effect as the coefficient of ρ_4 and σ_4 are significant (Column (6) in Table A5).

Figure 3 illustrates the marginal effects of temperature on output growth in poor regions, as well as the marginal effects of precipitation on output growth in rich regions. We use the two-lag model from column (3) in Tables 5 and 6 to analyze the marginal effects, as the region-weighted estimates treat all countries equally, rather than the estimate in column (6) that emphasizes regions with large populations. In addition, the results in column (3) are also more robust compared to those in column (6).

As Figure 3 shows, 1℃ increase in temperature significantly increases GDP per capita growth between two periods by 21.7% in poor regions with an average temperature of 10℃. Since we use three-year average data, this marginal estimate at 10℃ implies that 1℃ temperature rise increases annual GDP per capita growth by approximately 6.8%[7]. The current average temperature between 2013-2015 in poor regions is 21.5℃, with over 30% of poor regions' average temperature above the optimal temperature (19℃). Nonetheless, the negative marginal effects in hot regions are consistently insignificant.

For the marginal precipitation effect, the current average precipitation in rich regions is 1.0m, a further increase of 100mm in precipitation increases GDP per capita growth between two periods by 6.1% (approximately 2.0% annually). For Spain, Portugal, and Italy, which are located in southern Europe, rich, and expected to experience a precipitation decrease, the average precipitation is 700mm. 100mm decrease in precipitation in these countries is expected to reduce their annual GDP per capita growth by approximately 0.71%, a significant impact given their average annual GDP per capita growth rate of 2.5% from 2013 to 2015 [8].

D. Robustness checks

Alternative Specifications.—Table 7 presents the cumulative effects of temperature and precipitation on output growth based on the two-lag model with different fixed effects. Columns (1) and (5) use country and year fixed effects. Columns (2) and (6) are similar to columns (1) and (5) but further include subnational region fixed effects. Columns (3) and (7) are similar to columns (2) and (6) but

[7] $\sqrt[3]{1+0.217}-1 \approx 0.068$

[8] According to IPCC AR6 (IPCC et al., 2021), precipitation is expected to decrease by 10% to 20% (70mm to 140mm) in southern Europe under 2℃global warming scenario.

Table 6—Extended long difference results between poor and rich regions (continued)

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
$\Delta P^2 \times poor$	-0.0671	-0.0625	0.00244	-0.143**	-0.169***	-0.146**
	(0.0709)	(0.0664)	(0.0595)	(0.0650)	(0.0588)	(0.0730)
$L1 : \Delta P^2 \times poor$	-0.0350	-0.0504	-0.0745	-0.0187	-0.0669	-0.0840
	(0.0344)	(0.0759)	(0.1150)	(0.0588)	(0.0565)	(0.0899)
$\Delta P \times poor$	0.271	0.153	-0.0256	0.493*	0.739***	0.557*
	(0.3011)	(0.2991)	(0.2569)	(0.2763)	(0.2685)	(0.2917)
$L1 : \Delta P \times poor$	0.0435	0.00916	0.171	0.0512	0.220	0.458
	(0.144)	(0.297)	(0.405)	(0.168)	(0.174)	(0.300)
Sum of coeff. of ΔP^2 in Poor	-0.146	-0.198	-0.0301	-0.239	-0.372*	-0.310
	(0.138)	(0.237)	(0.423)	(0.178)	(0.214)	(0.426)
Sum of coeff. of ΔP in Poor	0.347	0.0476	-0.42	0.689	1.32	1.42
	(0.588)	(0.995)	(1.500)	(0.694)	(0.903)	(1.68)
$\Delta P^2 \times rich$	-0.0643	-0.148*	-0.171***	-0.218***	-0.150**	-0.0761
	(0.0874)	(0.0845)	(0.0647)	(0.0556)	(0.0698)	(0.0554)
$L1 : \Delta P^2 \times rich$	-0.0291	-0.0926	-0.134*	-0.0926*	-0.0996**	-0.108*
	(0.0568)	(0.0687)	(0.0736)	(0.0519)	(0.0481)	(0.0605)
$\Delta P \times rich$	0.166	0.485	0.573*	0.710***	0.558*	0.306
	(0.3802)	(0.4077)	(0.2968)	(0.2509)	(0.2907)	(0.2608)
$L1 : \Delta P \times rich$	0.146	0.323	0.639*	0.256	0.275	0.276
	(0.2772)	(0.3611)	(0.3795)	(0.1777)	(0.1874)	(0.2001)
Sum of coeff. of ΔP^2 in Rich	-0.183	-0.420*	-0.516**	-0.509***	-0.408**	-0.0568
	(0.21)	(0.232)	(0.252)	(0.131)	(0.187)	(0.191)
Sum of coeff. of ΔP in Rich	0.662	1.43	2.25*	1.58***	1.22*	0.128
	(0.898)	(1.15)	(1.21)	(0.515)	(0.682)	(0.781)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.276	0.352	0.511	0.319	0.429	0.611
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Table A5 provides complete regression results with all lags. Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

use poor×year fixed effects rather than year fixed effects. Columns (4) and (8) include subnational region, year, and region-specific time trend fixed. We find that when controlling only for country and year fixed effects, the cumulative effects of both temperature and precipitation on output growth are smaller than

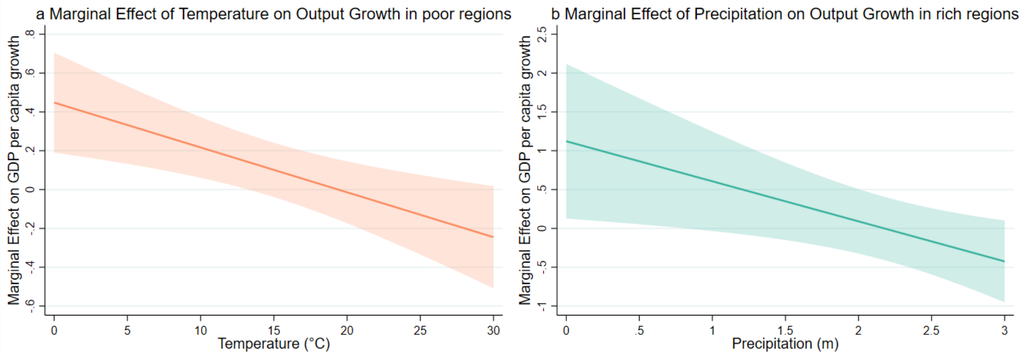

Figure 3. Marginal effects of temperature, precipitation on output Growth in Poor, rich Regions

Note: This figure shows the the marginal effects of temperature on GDP per capita growth in poor regions (left), and the marginal effects of precipitation on GDP per capita growth in rich regions (right) based on column (3) in Table 5 and Table 6. The shadow areas represent the 90% confidence interval.

those in our main specification results as shown in Tables 5 and 6. This may be because time-invariant factors at the subnational region level are not fully captured by country fixed effect. When we further include region fixed effects, as in columns (2) and (5), the results are almost identical to our main specification results. Since our main specification only includes year and region fixed effects, this result indicates that using subnational fixed effects alone is sufficient to control for time-invariant factors at both country and subnational levels. In addition, the results in columns (3) and (4), as well as in columns (7) and (8), are broadly consistent with our main specification results, although the standard error for the effect of precipitation in rich regions slightly increases in columns (4) and (8).

Bootstrap estimates.—As mentioned in the empirical results section, the statistical significance may be decreased due to more lags being included. To address this, we employ the bootstrap method as an alternative approach to estimate the cumulative effects. Specifically, we drew 1,000 samples of countries with replacements to quantify the uncertainty of the marginal effects. For each bootstrap iteration, we first categorize the observations into poor and rich regions using the same method described in the heterogeneity section. Then, we use the two-lag extended long-difference model based on region weighting to estimate the marginal effects. The results are depicted in Figure 4, with whiskers representing 95% confidence intervals. As the figure shows, both the marginal effects of temperature and precipitation are significant at low levels. The marginal effect of temperature at 10℃ is 0.225, whereas the marginal effect of precipitation at 1m is 0.645 (significant at 10%). These are almost identical to the point estimates in Figure 3, where the marginal effect of temperature at 10℃ is 0.217, and the marginal effect of precipitation at 1m is 0.61. This consistency suggests the robustness of

Table 7—Alternative Specifications of Extend Long Difference Results

	(1) Two-lag	(2) Two-lag	(3) Two-lag	(4) Two-lag	(5) Two-lag	(6) Two-lag	(7) Two-lag	(8) Two-lag
Sum of coeff. of ΔT^2 in Poor	-0.0154**	-0.0231***	-0.0235**	-0.0230**	-0.0000253	-0.00573	-0.00822	-0.00570
	(0.00629)	(0.00889)	(0.00921)	(0.0109)	(0.00392)	(0.00721)	(0.00699)	(0.00881)
Sum of coeff. of ΔT in Poor	0.587**	0.896***	0.928***	0.893**	-0.0542	0.263	0.173	0.262
	(0.233)	(0.313)	(0.326)	(0.384)	(0.131)	(0.215)	(0.200)	(0.263)
Sum of coeff. of ΔT^2 in Rich	-0.00877	-0.00435	-0.00618	-0.00438	0.0163**	0.0225**	0.0202*	0.0224
	(0.00842)	(0.0127)	(0.0129)	(0.0155)	(0.00664)	(0.0113)	(0.0112)	(0.139)
Sum of coeff. of ΔT in Rich	0.343	0.276	0.249	0.276	-0.439***	-0.490	-0.345	-0.490
	(0.281)	(0.46)	(0.46)	(0.563)	(0.133)	(0.319)	(0.300)	(0.392)
Sum of coeff. of ΔP^2 in Poor	0.0185	-0.0301	-0.0342	-0.0294	-0.0658	-0.0864	-0.122	-0.0855
	(0.138)	(0.423)	(0.419)	(0.520)	(0.124)	(0.306)	(0.313)	(0.375)
Sum of coeff. of ΔP in Poor	-0.291	-0.42	-0.41	-0.423	0.325	0.540	0.515	0.536
	(0.658)	(1.5)	(1.47)	(1.84)	(0.661)	(1.17)	(1.17)	(1.43)
Sum of coeff. of ΔP^2 in Rich	-0.322**	-0.516**	-0.453**	-0.518*	-0.172**	-0.244	-0.279	-0.244
	(0.141)	(0.252)	(0.234)	(0.309)	(0.0700)	(0.202)	(0.196)	(0.248)
Sum of coeff. of ΔP in Rich	1.28*	2.25*	2.05*	2.25	0.738**	0.757	0.959	0.757
	(0.694)	(1.21)	(1.16)	(1.49)	(0.372)	(0.809)	(0.761)	(0.993)
Obs.	4998	4998	4998	4998	4998	4998	4998	4998
R^2	0.408	0.511	0.513	0.511	0.350	0.612	0.615	0.611
Fixed effects	Cty,Yr	Cty,Reg,Yr	Cty,Reg,Poor-Yr	Reg,Yr,Reg-Yr-tr	Cty,Yr	Cty,Reg,Yr	Cty,Reg,Poor-Yr	Reg,Yr,Reg-Yr-tr
Weight	Region	Region	Region	Pop.	Pop.	Pop.		

Note: Specification (1) and (5) include the country and year fixed effects. Specifications (2) and (6) include the country, region, and year fixed effects. Specifications (3) and (7) include the country, region, and poor×year fixed effects. Specifications (4) and (8) include the region, year, and region-specific time trend fixed effects. Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

our findings.

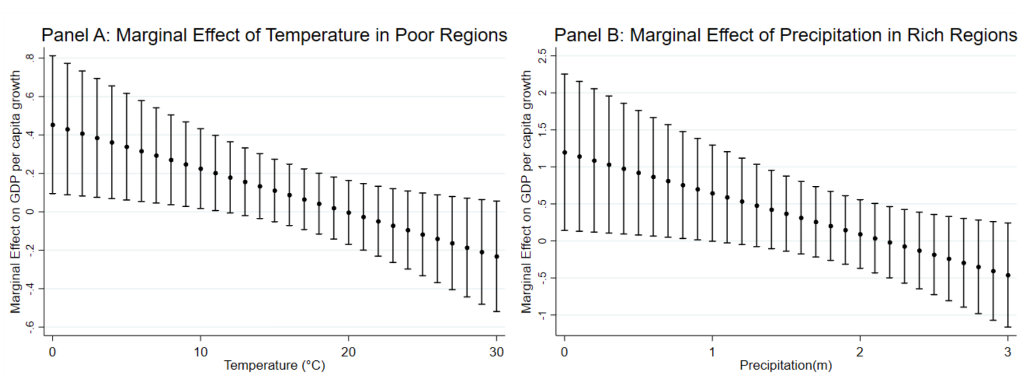

Figure 4. Bootstrapped Estimates of Marginal Effects of Temperature, Precipitation on Output Growth

Note: Figure 4 shows the bootstrapped estimates of marginal effects of temperature on GDP per capita growth in rich regions (left) and the bootstrapped estimates of marginal effects of precipitation on GDP per capita growth in poor regions (right). Dots are the mean values of the 1000 bootstrapped estimates. The whiskers represent 95 percent confidence intervals.

Climate variation effects.—In addition to the impacts of annual average temperature and precipitation, a growing body of literature has identified significant effects of intra-annual variations in temperature and precipitation on economic output. To control these effects, we extend the vector $\mathbf{T_{ip}}$ in our regression model (Equation 12) from (T_{ip}, P_{ip}) to $(T_{ip}, P_{ip}, AST_{ip}, ASP_{ip})$. The annual temperature variability AST_{it} and precipitation variability ASP_{it} are measured by Anomaly Standardized Temperature and Anomaly Standardized Precipitation, respectively. They are defined as the annual sum of monthly temperature or rainfall anomalies from their climatological means, which is proposed by Lyon and Barnston (2005). They measure the deviation of temperature or precipitation in a specific month of a given year from the long-term average of temperature and precipitation for that month. Both indicators follow a normal distribution with a mean of 0, where higher values of AST_{it} or ASP_{it} (>0) suggest the potential occurrence of heatwaves or floods, while lower values of AST_{it} or ASP_{it} (<0) indicate the likelihood of cold snaps or droughts. Appendix III provides an illustration of these metrics in detail.

Table A6 presents the regression results considering annual average temperature and precipitation, as well as the intra-annual temperature and precipitation variations. We find that the cumulative effect of annual temperature in poor regions remains significant when using the region-weighed two-lag model (Column (3) in Table A6). Including variability factors slightly increases the magnitude of the marginal effect. 1℃ increase in temperature increases GDP per capita growth between two periods by 23.2% in poor regions with an average temperature of 10℃, 1.5% higher than the result based on our main specification as depicted in Figure 3. The summed coefficients of precipitation also stable and broadly consistent with the results in column (3) of Table 6, but the standard errors increased.

Looking for the effects of temperature and precipitation variations on output growth in Table 8 (subset from Table A6 with summed coefficients of intra-annual temperature and precipitation variations), most of the summed coefficients are stable or have increased in absolute value after accounting for more lagged effects. However, all of them lack statistical significance. Focusing on the region-weighted results in Column (3), we observe positive trends in the effect of temperature variation on output growth in both poor and rich regions, as the summed coefficients of quadratic terms are positive and have increased. Additionally, precipitation variation appears to have a limited impact on output growth in poor regions, while it shows a negative growth effect in rich regions, with the summed coefficients being negative and increasing in absolute value.

IV. Adaptation and Future damage

A. Adaptation

Table A2 presents the short-term effects of weather conditions on output in poor and rich regions, based on the panel model in Equation (13). We find that

Table 8—Effects of Climate Variations on Output Growth in Rich and Poor Regions

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
Sum of coeff. of ΔAST^2 in poor	0.0134	0.0437**	0.0422	-0.0328	0.00529	0.0245
	(0.0125)	(0.0171)	(0.0313)	(0.0137)	(0.0336)	(0.0518)
Sum of coeff. of ΔAST in poor	0.0389	0.0408	-0.00905	0.138***	0.0943*	0.0187
	(0.0309)	(0.0467)	(0.092)	(0.043)	(0.0527)	(0.174)
Sum of coeff. of ΔAST^2 in rich	0.00354	0.0372	0.0486	-0.0204	-0.00427	-0.00892
	(0.0271)	(0.035)	(0.0498)	(0.0229)	(0.0334)	(0.0446)
Sum of coeff. of ΔAST in rich	0.0128	0.0852	0.159	0.0167	0.117	0.165
	(0.0747)	(0.101)	(0.158)	(0.0467)	(0.0714)	(0.128)
Sum of coeff. of ΔASP^2 in poor	0.0621***	0.0457*	0.0173	0.0397	0.0467	-0.0549
	(0.02)	(0.0259)	(0.0531)	(0.0328)	(0.0512)	(0.0701)
Sum of coeff. of ΔASP in poor	-0.00877	-0.0503	-0.143	0.0476	0.0308	-0.0265
	(0.0603)	(0.109)	(0.143)	(0.0638)	(0.0907)	(0.142)
Sum of coeff. of ΔASP^2 in rich	0.0112	-0.00515	-0.0832	0.0221	-0.00821	-0.0229
	(0.0425)	(0.0616)	(0.0827)	(0.0228)	(0.041)	(0.0637)
Sum of coeff. of ΔASP in rich	-0.000254	-0.0997	-0.106	0.0784	0.229***	0.158*
	(0.0744)	(0.107)	(0.16)	(0.0684)	(0.0829)	(0.0916)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.295	0.381	0.545	0.347	0.453	0.640
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Standard errors clustered at the country level are in parentheses. Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. ***p <0.01, **p <0.05, *p <0.10

the effect of temperature on output growth is nearly identical in both rich and poor regions [9]. This is consistent with previous studies, which suggest that the vulnerability of poor countries to weather conditions is primarily due to higher temperatures rather than their economic status (Burke, Hsiang and Miguel, 2015; Mendelsohn, Dinar and Williams, 2006). 1℃ temperature increase at 26℃ de-

[9] This finding is consistent in both region- and population-weighted regression results. However, we also find that precipitation has significant effects on output levels in poor regions when weighted by population, while these effects are insignificant in rich regions.

creases GDP per capita growth by 1.8% in poor regions and 1.7% in rich regions when weighted by regions. However, the extended long-difference model suggests that the effect of temperature in rich regions is insignificant. This disparity between short-term and medium-term effects in rich regions indicates that rich regions have developed adaptations to mitigate the substantial short-term negative effects of temperature.

For the adaptation in poor regions, Figure 5 shows the marginal effect of temperature on output growth based on the panel model from column 2 in Table A2 and the extended long-difference model from column (3) in Table 5. We convert the marginal growth effect between periods to an annual average marginal growth effect using $\sqrt[3]{1+\hat{\tau}}-1$, where $\hat{\tau}$ represents the marginal estimates based on the extended long-difference model. We find that the effect of temperature on poor regions intensifies over time. The positive medium-term effect of temperature is approximately 5 to 10 times greater than the short-term effect for low temperature levels. 1℃ increase at 10℃ increase short-term output growth by 0.69%, but this expands to 6.8% for medium-term output growth. This suggests that poor regions with low temperature levels develop adaptations from short-term to medium-term, thereby increasing the benefits of temperature increases.

To quantify the uncertainty of the adaptation estimate, we bootstrap our data 1000 times and calculate the ratio of short-term to medium-term marginal effects of temperature $((\sum^{l}(2\times\rho_l T^{*}+\sigma_l))/(2\times\gamma T^{*}+\delta))$ for each iteration [10], as suggested by Burke and Emerick (2016). Panel B in Figure 5 shows the bootstrap results. We find that the confidence intervals are above zero at low temperature levels, suggesting significant adaptation to the temperature change in poor regions. For temperatures above 20℃, although there is a trend suggesting that medium-term negative effects are higher than short-term effects, all confidence intervals span zero, suggesting that the increase in temperature does not significantly heighten medium-term damage in hot poor regions.

For adaptation to precipitation, we find no significant short-term growth effects in either rich or poor regions (column 2 in Table A2). However, the extended long-difference model shows a significant effect that medium-term output growth in almost all regions benefits from increased precipitation, suggesting that rich regions have developed adaptations to capitalize on increased precipitation.

B. Future Damage

In this section, we project output losses under a future 2.0℃ global warming scenario, based on the results from the extended long-difference and panel regression models. We consider the shared socioeconomic pathway of sustainability (SSP1) scenario as the future baseline population and GDP growth trajectory, and the SSP1-26 scenario as the future global warming tendency, as the SSP1-26 scenario's global warming projections are most consistent with the 2.0℃ global

[10] The bootstrap method used here is the same as that in robustness checks section

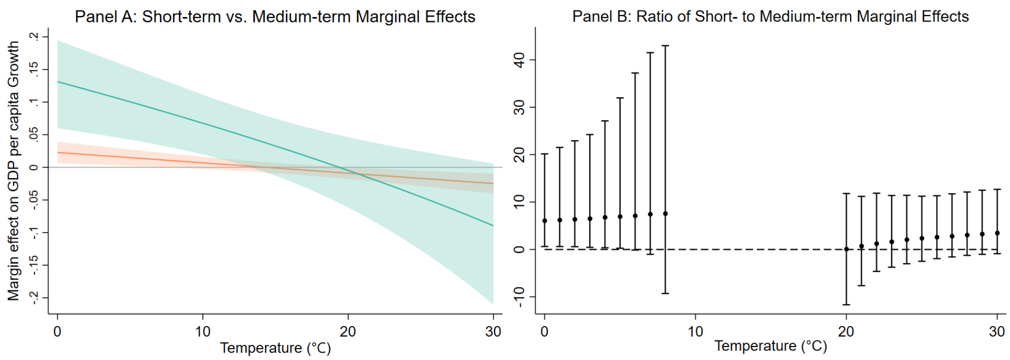

FIGURE 5. SHORT-TERM AND MEDIUM-TERM MARGINAL EFFECTS OF TEMPERATURE IN POOR REGIONS

Note: Figure 5 shows the short-term and medium-term marginal effects of temperature in poor regions (left), as well as the ratio between them (right). The orange line represents the short-term marginal effect, whereas the green line represents the medium-term marginal effect. The shadow areas represent the 90% confidence interval and the whiskers represent the fifth to ninety-fifth percentile. The ratios between 9℃ to 19℃ are omitted due to the extreme values generated when the short-term effect is close to zero.

warming target considered by latest Intergovernmental Panel on Climate Change (IPCC) reports (IPCC et al., 2021). We also consider a probabilistic framework to account for uncertainties in the historical relationship between temperature and economic growth, as well as the spatial pattern of future mean annual temperature change associated with a given level of aggregate emissions, as suggested by Burke, Davis and Diffenbaugh (2018). In particular, we use the bootstrapped estimates from Figure 4 to account for the first set of probabilities. The second set comes from using SSP1-26 future global climate data, which includes 186 global climate simulations from 13 Earth system models from the sixth phase of the Coupled Model Intercomparison Project (CMIP6). In this case, there are 186,000 possible output losses in total based on permutations of bootstrapped estimates and climate emulations.

For each bootstrap run b and climate emulation c, GDP per capita y in each future year $t+1$ for region i is projected using the following equation:

$$y_{it+1}^{bc} = y_{it}^{bc} \times (1 + \lambda_{it+1} + \phi_{it+1}^{bc}) \tag{14}$$

Where λ_{it+1} is the baseline GDP per capita growth projected by the GDP and population data corresponding to the SSP1 scenario. $\phi_{it+1}^{bc} = g^b(\mathbf{T^c_{it+1}}) - g^b(\mathbf{T^c_{i0}})$ is the additional estimated change in the GDP per capita growth g due to the projected temperature or precipitation increase above baseline climate $\mathbf{T_{i0}}$. $g^b(\mathbf{T^c_{it+1}})$ is estimated based on the extended long-difference model or panel model for each bootstrap run b and climate emulation c. The percentage change in GDP per capita is calculated by: $y_{it}^{bc}/y_{it} - 1$, where y_{it} is the baseline GDP per capita under the SSP1 scenario.

In practice, we randomly draw 1000 samples from bootstrapped estimates and climate emulations to calculate the uncertainty of percentage change in GDP per capita[11]. For each iteration, we first calculate the average of temperature or precipitation from 2015 to 2017 for each emulation as the baseline climate condition. Then, GDP per capita is calculated year by year for each region. To consistent with the extended long-difference regression results, regions in the current year are categorized as rich or poor based on whether their projected GDP per capita in the last year exceeds the historical global median. The temperature effect estimate is applied to rich regions, while the precipitation effect estimate is applied to poor regions. We also use a three-year moving average for temperature and precipitation to match the values used in the extended long-difference regression. For projections based on panel estimates, the same categorization is used, but ϕ^{bc}_{it+1} is calculated based only on the temperature impact.

The projected GDP per capita changes based on our extended long-difference and panel models are given in Table 9 and shown graphically in Figure 6. According to the extended long-difference model, global average GDP per capita is projected to decrease by 11.8% to 19.4% due to temperature changes, compared to a scenario with no additional climate change from 2015 to 2017 onward. This is lower than the panel estimate, which projects a decrease of 16.0% to 22.9%. This is because the temperature impact based on extended long-difference estimates only acts on poor regions, while the panel estimates affect both poor and rich regions. In contrast, the change in precipitation is projected to increase global average GDP per capita by 6.8% to 23.5%.

Considering the total temperature and precipitation impacts, the projected changes in global average GDP per capita vary significantly depending on the statistical approach used. The global average GDP per capita is projected to decrease by 1.8% when weighted by subnational regions but is projected to increase by 9.6% to 16.9% when weighted by population or baseline GDP per capita. These findings suggest that although most *regions* are expected to experience a decline in GDP per capita, most *populations* and rich regions are expected to see increases. This implies that the gap between rich and poor regions will widen further, with rich regions benefiting from increased precipitation and poor regions suffering from rising temperatures.

Figure 7 illustrates the percentage change in GDP per capita for each region. In some rich countries, like Canada and northern European nations, the effects of temperature on them are limited, but the increased precipitation is expected to boost their economic output, leading to a considerably increased GDP per capita. Other rich countries, such as the United States and Australia, may see stable GDP per capita due to consistent precipitation levels. In contrast, most

[11]The complete sampling approach ensures a thorough sampling of the full uncertainty space but also quickly leads to computer memory issues. Alternatively, we draw various samples from 100 to 1500. The results show that the distribution of the uncertainty has been stable after 1000 samples, see Figure A2 in the appendix for sampling results

TABLE 9—PERCENTAGE CHANGES IN GDP PER CAPITA IN 2100 FOR SSP1-126 SCENARIO

	Extended long difference estimates			Panel estimate		
	(1) region weighted	(2) population weighted	(3) GDPpc weighted	(4) region weighted	(5) population weighted	(6) GDPpc weighted
Change in GDP per capita from temperature (%)	-19.4	-16.0	-11.8	-22.9	-17.2	-16.0
Change in GDP per capita from precipitation (%)	6.8	23.5	10.2			
Change in GDP per capita in total (%)	-1.8	16.9	9.6			

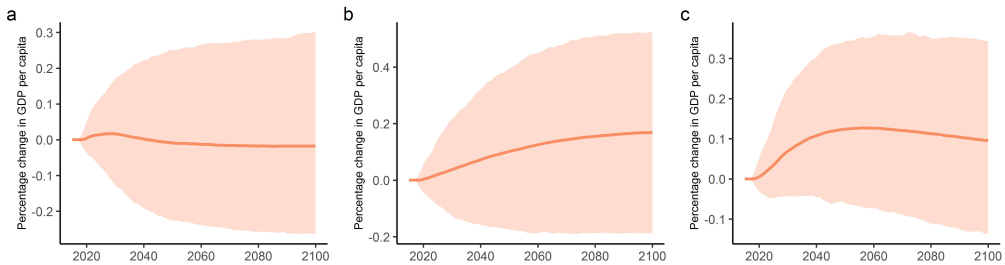

FIGURE 6. PROJECTED GDP PER CAPITA CHANGES DUE TO TEMPERATURE AND PRECIPITATION MEDIUM-TERM EFFECTS

Note: Figure 6 shows the projected percentage changes in GDP per capita based on different statistical approaches under the SSP1-126 scenario. Panel A (left) is the projection weighted by the inverse of the number of subnational regions in a country. Panel B (medium) is the projection weighted by population in each region. Panel C (right) is the projection weighted by the baseline GDP per capita of each region. The shadow areas represent the fifth to ninety-fifth percentile.

poor countries are hot, particularly those in Africa, thus they are expected to experience GDP per capita reductions due to rising temperatures. Although their GDP per capita could exceed the global historical median value, the benefit from the precipitation is limited and short in time. India, in contrast, the reduction of its GDP per capita due to increased temperature is expected to be fully offset by increased precipitation.

V. Discussion and Conclusion

Quantitative estimates of climate change's impact on economic output are crucial for public policy, informing decisions about investments in both emissions reductions and in measures to help economies adapt to a changing climate. While existing literature has explored the relationship between climate and economic output, the findings have often been ambiguous. Previous studies have also encountered some methodological challenges. This study consolidates the approaches used in prior studies and provides new estimates about the effects of both temperature and precipitation on GDP per capita.

Using a global sub-national database from over 1600 regions in 196 countries,

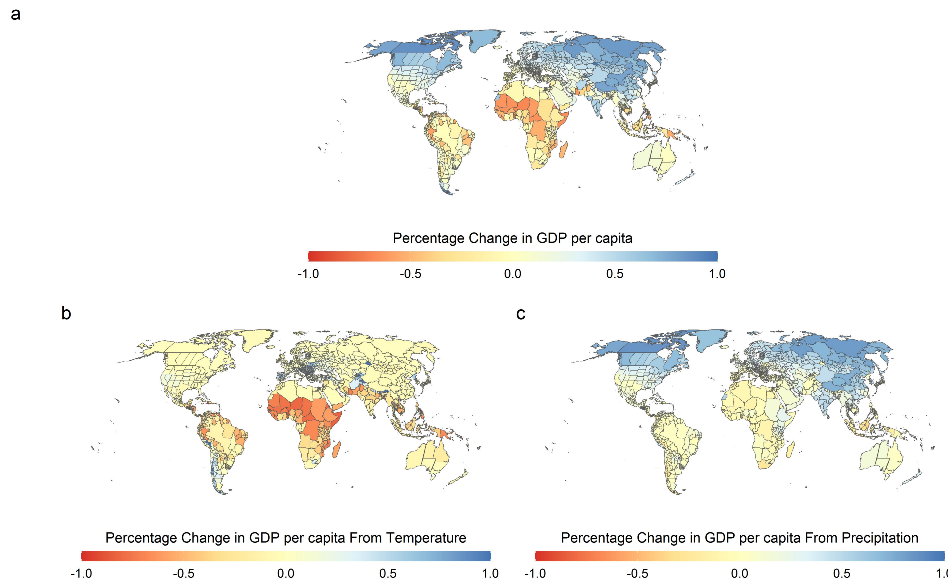

Figure 7. Region-level projected GDP per capita changes due to temperature and precipitation medium-term effects

Note: Figure 7 shows the region-level projected GDP per capita changes due to the temperature and precipitation medium-term effects. Panel A shows the projected results considering both the temperature and precipitation effects. Panel B shows the projected results considering the effect of temperature only. Panel C shows the projected results considering the effect of precipitation only.

we first conduct a fixed-effects panel regression on temperature, precipitation, and GDP per capita. We find a significant effect of temperature on output growth. One degree increase in temperature is expected to reduce GDP per capita growth by 1.6% in hot regions. This contrasts with the findings of Kalkuhl and Wenz (2020), who used subnational data from 77 countries and reported no significant growth effect of temperature. The average temperature and GDP per capita (weighted by regions) for these 77 countries are 13.5°Cand \$19639, while they are 18.6°C and \$14857 for 196 countries. Therefore, Kalkuhl and Wenz (2020) results may underestimate the effect of temperature due to the lack of data from hot and poor regions. In addition, while most studies find there is no effect of precipitation on output and just use it as a control variable, we find a significant positive effect of precipitation on output growth for large population regions. This result supports the findings of Damania, Desbureaux and Zaveri (2020), who suggested that using aggregated data from larger spatial scales may mask the heterogeneous effects of weather, emphasizing the importance of using finer-scale data in climate economic studies.

To address time-invariant factors relevant to output growth, we developed an extended long-difference model by conducting a second difference for the standard long-difference model. The results based on this model show a significant effect of temperature on medium-term output growth in poor regions. The optimal temperature for poor regions is 19℃, which is higher than that revealed by panel models (15℃). In addition, the medium-term marginal effect of temperature is significantly higher than the short-term marginal effect at lower temperature levels. 1℃ increase at 10℃ increase short-term output growth by 0.69%, but this effect expands to 6.8% for medium-term output growth. This suggests that poor regions have developed adaptations to capitalize on increased precipitation. Although the negative medium-term marginal effect also expanded in hot regions, its statistical significance weakens. Regarding the effects of precipitation, a 100 mm increase in precipitation at current rich regions' average precipitation increases annual GDP per capita growth by approximately 2.0%. This positive effect of precipitation is consistent under different precipitation levels, although the marginal effect of this effect decreases. We find no significant effects of temperature in rich regions or precipitation in poor regions.

Using climate change projection from 186 emulations, we project potential changes in GDP per capita by the century's end. If the global temperature increase 2.0℃ in 2100, the global average GDP per capita is projected to increase by 9.6% compared to a scenario with no additional climate change from 2015 to 2017 onward. However, this increase is largely driven by the positive effect of increased precipitation in rich regions. If we only consider the effect of temperature on poor regions, the global average GDP per capita is projected to decline by 11.8-19.4%. Since rich countries are affected only positively by precipitation and poor countries only negatively by temperature, it is expected that rich countries get richer and poor countries get poorer in the future.

A caveat for this work needs to be made clear. Due to the data limitation, we use three-year averages and two-period differences for the extended long-difference regressions. These estimates primarily capture medium-term adaptations to climate change over a six- to nine-year period. Since adaptation processes may require longer periods, further research with extended time series data is necessary to fully understand the long-term effects of climate change on economic output.

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Mathematical Appendix: The Effects of Climate Conditions

Jinchi Dong, Richard S.J. Tol, Jinnan Wang

Appendix I: Dynamic Regression Model

This section discusses a more general econometric model for identifying the effects of climate conditions on output in the context of a dynamic growth equation, following the derivation in Dell, Jones and Olken (2012). If we consider l lags of climate effects, the relationship between average output per capita and climate conditions is given by:

$$ln(\overline{y_{ip}}) = c_i + \alpha_0\overline{T^2_{ip}} + \cdots + \alpha_l\overline{T^2_{ip-l}} + \beta_0\overline{T_{ip}} \cdots + \beta_l\overline{T_{ip-l}} + ln(\overline{A_{ip}}) \tag{A1}$$

The relationship between the growth of productivity and climate conditions is given by:

$$\Delta ln(\overline{A_{ip}}) = g_i + \gamma_0\overline{T^2_{ip}} + \cdots + \gamma_l\overline{T^2_{ip-l}} + \delta_0\overline{T_{ip}} + \cdots + \delta_l\overline{T_{ip-l}} \tag{A2}$$

Taking the first difference of Equation (A1) between period p and period $p-2$ yields:

$$\begin{aligned}
&\overline{g_{ip}} = ln(\overline{y_{ip}}) - ln(\overline{y_{ip-2}})\\
&= \alpha_0(\overline{T^2_{ip}} - \overline{T^2_{ip-2}}) + \cdots + \alpha_l(\overline{T^2_{ip-l}} - \overline{T^2_{ip-l-2}})\\
&+ \beta_0(\overline{T_{ip}} - \overline{T_{ip-2}}) + \cdots + \beta_l(\overline{T_{ip}} - \overline{T_{ip-l-2}}) + (ln(\overline{A_{ip}}) - ln(\overline{A_{ip-2}}))\\
&= \alpha_0\Delta\overline{T^2_{ip}} + \cdots + \alpha_l\Delta\overline{T^2_{ip-l}} + \beta_0\Delta\overline{T_{ip}} + \cdots + \beta_l\Delta\overline{T_{ip-l}} + \Delta ln(\overline{A_{ip_2}})
\end{aligned} \tag{A3}$$

Taking the additional difference of Equation (A3) between period p and period $p-2$ yields:

$$\begin{aligned}
\Delta\overline{g_{ip}} = \overline{g_{ip}} - \overline{g_{ip-2}} = &\\
&\alpha_0\Delta\overline{T^2_{ip}} + \alpha_1\Delta\overline{T^2_{ip-1}} +\\
&(\alpha_2 - \alpha_0)\Delta\overline{T^2_{ip-2}} + \cdots - \alpha_{l-1}\Delta\overline{T^2_{ip-l-1}} - \alpha_l\Delta\overline{T^2_{ip-l-2}} +\\
&\beta_0\Delta\overline{T_{ip}} + \beta_1\Delta\overline{T_{ip-1}} +\\
&(\beta_2 - \beta_0)\Delta\overline{T_{ip-1}} + \cdots - \beta_{l-1}\Delta\overline{T_{ip-l-1}} - \beta_l\Delta\overline{T_{ip-l-2}} +\\
&(\Delta ln(\overline{A_{ip_2}}) - \Delta ln(\overline{A_{ip_2-2}}))
\end{aligned} \tag{A4}$$

The difference of Equation (A2) between period p and period $p-2$ is given by:

$$\begin{aligned}
\Delta ln(\overline{A_{ip_2}}) = \Delta ln(\overline{A_{ip}}) - \Delta ln(\overline{A_{ip-2}}) = \sum_{j=0}^{1} \Delta ln(\overline{A_{ip-j}})&\\
= \gamma_0\overline{T^2_{ip}} + (\gamma_0 + \gamma_1)\overline{T^2_{ip-1}} + \cdots + (\gamma_l + \gamma_{l-1})\overline{T^2_{ip-l}} + \gamma_l\overline{T^2_{ip-l-1}}&\\
+ \delta_0\overline{T_{ip}} + (\delta_0 + \delta_1)\overline{T_{ip-1}} + \cdots + (\delta_l + \delta_{l-1})\overline{T_{ip-l-1}} + \delta_0\overline{T_{ip-l-1}}&
\end{aligned} \tag{A5}$$

Therefore, the difference of Equation (A5) between period p and period $p-2$ is

given by:
(A6)

$$\begin{aligned}\Delta ln(\overline{A_{ip_2}}) - \Delta ln(\overline{A_{ip_2-2}}) \\ &= \gamma_0 \Delta \overline{T_{ip}^2} + (\gamma_0 + \gamma_1)\Delta \overline{T_{ip-1}^2} + \cdots + (\gamma_l + \gamma_{l-1})\Delta \overline{T_{ip-l}^2} + \gamma_l \Delta \overline{T_{ip-l-1}^2} \\ &+ \delta_0 \Delta \overline{T_{ip}} + (\delta_0 + \delta_1)\Delta \overline{T_{ip-1}} + \cdots + (\delta_l + \delta_{l-1})\Delta \overline{T_{ip-l-1}} + \delta_l \Delta \overline{T_{ip-l-1}}\end{aligned}$$

Substituting equation (A6) into (A4) yields:
(A7)

$$\begin{aligned}\Delta \overline{g_{ip}} =& \overline{g_{ip}} - \overline{g_{ip-2}} = \\ & (\alpha_0 + \gamma_0)\Delta \overline{T_{ip}^2} + (\alpha_1 + \gamma_0 + \gamma_1)\Delta \overline{T_{ip-1}^2} + \cdots + \\ & (\alpha_l + \gamma_{l-1} + \gamma_l - \alpha_{l-2})\Delta \overline{T_{ip-l}^2} + (\gamma_l - \alpha_{l-1})\Delta \overline{T_{ip-l-1}^2} - \alpha_l \Delta \overline{T_{ip-l-2}^2} + \\ & (\beta_0 + \delta_0)\Delta \overline{T_{ip}} + (\beta_1 + \delta_0 + \delta_1)\Delta \overline{T_{ip-1}} + \cdots + \\ & (\beta_l + \delta_{l-1} + \delta_l - \beta_{l-2})\Delta \overline{T_{ip-l}} + (\delta_l - \beta_{l-1})\Delta \overline{T_{ip-l-1}} - \beta_l \Delta \overline{T_{ip-l-2}}\end{aligned}$$

Equation (A7) is the model used for our regressions.

if $l = 1$, Equation (A7) simplifies to:
(A8)

$$\begin{aligned}\Delta \overline{g_{ip}} =& \overline{g_{ip}} - \overline{g_{ip-2}} = \\ & (\alpha_0 + \gamma_0)\Delta \overline{T_{ip}^2} + (\alpha_1 + \gamma_0 + \gamma_1)\Delta \overline{T_{ip-1}^2} + (\gamma_1 - \alpha_0)\Delta \overline{T_{ip-2}^2} - \alpha_1 \Delta \overline{T_{ip-3}^2} + \\ & (\beta_0 + \delta_0)\Delta \overline{T_{ip}} + (\beta_1 + \delta_0 + \delta_1)\Delta \overline{T_{ip-1}} + (\delta_1 - \beta_0)\Delta \overline{T_{ip-2}} - \beta_i \Delta \overline{T_{ip-3}}\end{aligned}$$

Equation (A8) includes 8 terms with 6 lag terms. If we consider l lags of climate effects, the regression specification would have $2 \times (l + 3)$ terms with $2 \times (l + 2)$ lag terms.

Appendix II: Stationary Check

Figure A1 shows the mean values of the differences in temperature, precipitation, and interperiod GDP per capita growth over periods. As the figure shows, all the variables fluctuate around 0, suggesting that they are all trend-stationary.

We also conducted a unit root test to further check whether the variables are stationary. Since our panel data is a short panel with large cross-sections but short periods, we employ the Harris-Tzavalis test for this check. The results are shown in Table A1, we find that all the variables significantly reject the null hypothesis, confirming the stationarity of the variables.

Appendix III: Intra-annual weather variability

The Anomaly Standardized Precipitation (ASP) and Anomaly Standardized Temperature (AST) indexes used in this study originate from the Weighted Anomaly Standardized Precipitation (WASP) proposed by Lyon and Barnston

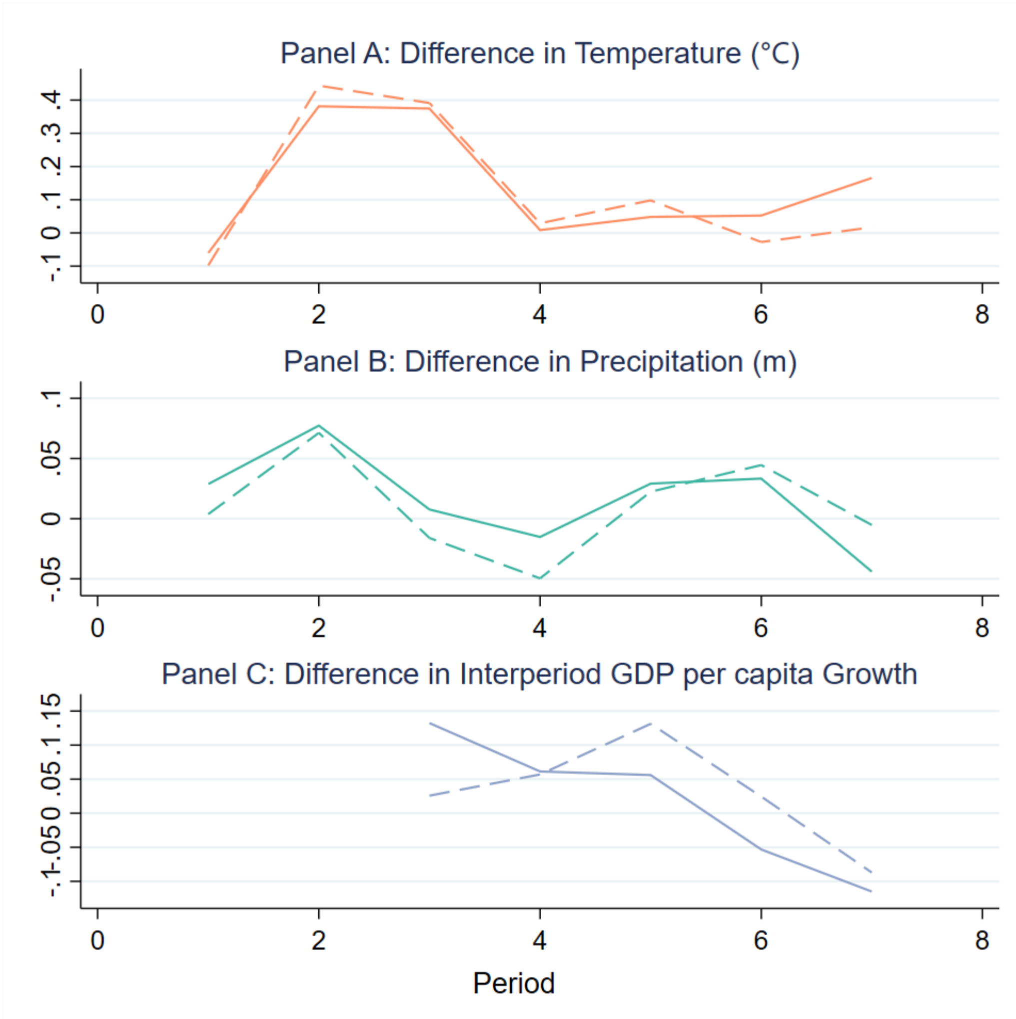

FIGURE A1. DIFFERENCES IN TEMPERATURE, PRECIPITATION, AND GDP PER CAPITA GROWTH OVER PERIODS.

Note: Figure S1 shows the difference in temperature, precipitation, and interperiod GDP per capita growth over periods. The solid lines represent the region-weighted average data. The dash lines represent the pop-weighted average data.

(2005). WASP is defined as the annual sum of monthly rainfall anomalies from their climatological means, weighted by the climatological contribution of monthly precipitation to the annual precipitation:

$$WS_{r,y} = \sum_{m=1}^{12} \frac{P_{r,m,y} - \overline{P}_{r,m}}{\sigma_{r,m}} \cdot \frac{\overline{P}_{r,m}}{\overline{PA}_r} \quad \text{(A9)}$$

TABLE A1—UNIT ROOT TEST RESULTS

	ΔT_{ip}	ΔP_{ip}	Δg_{ip}
HT test	-0.188***	-0.061***	0.288***

Note: The HT test refers to the Harris-Tzavalis test, which subtracts cross-sectional means. The null hypothesis of this test is that all panels contain unit roots. The value in the table represents the ρ statistic results. ***p <0.01

Where $WS_{r,y}$ is the weighted standardized monthly precipitation deviation in region r and year y. $P_{r,m,y}$ is the monthly total precipitation in region r, month m and year y. $\overline{P}_{r,m}$ is the historical mean of monthly total precipitation over the study year, $\sigma_{r,m}$ is the historical standard deviation of monthly total precipitation in that region, and $\overline{PA_r}$ is the historical mean of annual total precipitation in that region. The annual $WS_{r,y}$ is further standardized by the standard deviation of $WS_{r,y}$ in a given region over time to obtain a measure of the relative severity of annual precipitation surpluses or deficits:

$$WASP_{r,y} = \frac{WS_{r,y}}{\sigma_{S_r}} \tag{A10}$$

A WASP value greater than 0 indicates precipitation above the prevailing historical climate conditions, and vice versa. Although the WASP index is primarily designed for precipitation, it can also be adapted for temperature, forming the Weighted Anomaly Standardized Temperature (WAST), as discussed by Holtermann (2020). In addition, the WASP was initially designed for tropical regions, where the climate is distinctly divided into rainy and dry seasons. The weighting factor $\frac{\overline{P}_{r,m}}{\overline{PA_r}}$ is used to dampen large standardized anomalies resulting from small precipitation amounts occurring near the start or end of dry seasons and to emphasize anomalies during the core rainy seasons. However, as the climate in most parts of the world cannot be simplified into rainy and dry seasons, the weighting factor may introduce problematic effects by emphasizing deviations in months with higher precipitation totals (Holtermann, 2020). Therefore, we omitted the weighting factor in our analysis. The indexes we used are defined as follows:

$$S_{r,y} = \sum_{m=1}^{12} \frac{T_{r,m,y} - \overline{T}_{r,m}}{\sigma_{r,m}} \tag{A11}$$

$$AST_{r,y} = \frac{S_{r,y}}{\sigma_{S_r}} \tag{A12}$$

Where $S_{r,y}$ is the standardized monthly precipitation deviation in region r and year y. $T_{r,m,y}$ is the monthly total precipitation or monthly mean temperature in region r, month m and year y. $\overline{T}_{r,m}$ is the historical mean of monthly total precipitation or monthly mean temperature over 25 years. $\sigma_{r,m}$ is the historical standard deviation, for 25 years, of monthly total precipitation or monthly mean temperature in that region. The annual $S_{r,y}$ is further standardized by its standard deviation σ_{S_r} over 25 years to obtain the Anomaly Standardized Temperature and Anomaly Standardized Precipitation $AST_{r,y}$.

Appendix IV: Supplementary Tables and Figures

Table A2—Panel regression results between poor and rich regions

	(1)	(2)	(3)	(4)
Dep. var.	Annual GDP per capita growth			
	rich	poor	rich	poor
$\Delta T \times D$	-0.00880	-0.00224	-0.000848	0.00327
	(0.0060)	(0.0077)	(0.0035)	(0.0053)
$\Delta T \cdot T \times D$	0.000850	0.000161	0.000174	0.0000809
	(0.0005)	(0.0004)	(0.0002)	(0.0003)
$\Delta P \times D$	-0.0105	0.00774	0.000659	0.0357**
	(0.0096)	(0.0150)	(0.0088)	(0.0182)
$\Delta P \cdot P \times D$	0.00435	-0.00819	-0.00443	-0.0200***
	(0.0038)	(0.0068)	(0.0046)	(0.0075)
$T \times D$	0.0228**	0.0228**	0.00503	0.00391
	(0.0094)	(0.0099)	(0.0040)	(0.0039)
$T^2 \times D$	-0.000767***	-0.000794***	-0.000210*	-0.000188
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
$P \times D$	0.0130	0.0198	0.0166	0.0114
	(0.0153)	(0.0183)	(0.0135)	(0.0122)
$P^2 \times D$	-0.00372	-0.00425	-0.00193	-0.00110
	(0.0037)	(0.0045)	(0.0034)	(0.0029)
Obs.	41650		41650	
R^2	0.216		0.330	
Region FE	YES		YES	
Year FE	YES		YES	
Region-specific time trend FE	YES		YES	
Weight	Region		Pop.	

Note: D equals 1 for columns (2) and (4) and represents the results for poor regions, whereas D equals 0 for columns (1) and (4) and represents the results for rich regions. Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

Table A3—Extend long difference results with all variables

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
ΔT^2	-0.00495***	-0.00503**	-0.00535**	-0.00295***	-0.00325**	-0.00364***
	(0.0013)	(0.0021)	(0.0024)	(0.0009)	(0.0015)	(0.0009)
$L1 : \Delta T^2$	-0.00629***	-0.00423***	-0.00237	-0.00306**	-0.00158*	-0.000437
	(0.0015)	(0.0016)	(0.0020)	(0.0012)	(0.0009)	(0.0013)
$L2 : \Delta T^2$	-0.00134	-0.00553***	-0.00173	-0.000112	-0.00200	0.00189
	(0.0013)	(0.0021)	(0.0023)	(0.0012)	(0.0023)	(0.0027)
$L3 : \Delta T^2$		-0.000889	-0.00453*		0.00237*	0.000886
		(0.0018)	(0.0026)		(0.0014)	(0.0020)
$L4 : \Delta T^2$			0.000308			0.00114
			(0.0017)			(0.0022)
ΔT	0.186***	0.126*	0.175*	0.0867**	0.0482	0.0877**
	(0.0447)	(0.0740)	(0.0946)	(0.0354)	(0.0609)	(0.0395)
$L1 : \Delta T$	0.240***	0.101*	0.0138	0.0802*	0.0198	0.0190
	(0.0631)	(0.0522)	(0.0615)	(0.0476)	(0.0521)	(0.0631)
$L2 : \Delta T$	0.0532	0.192***	0.106	-0.00648	0.0392	-0.0610
	(0.0471)	(0.0715)	(0.0871)	(0.0315)	(0.0593)	(0.0726)
$L3 : \Delta T$		0.0242	0.191**		-0.0770*	0.0223
		(0.0613)	(0.0966)		(0.0453)	(0.0611)
$L4 : \Delta T$			0.0403			-0.00771
			(0.0641)			(0.0632)
ΔP^2	-0.0238	-0.115**	-0.106**	-0.0558*	-0.145***	-0.0978**
	(0.0289)	(0.0565)	(0.0433)	(0.0325)	(0.0412)	(0.0424)
$L1 : \Delta P^2$	-0.0442	-0.0851	-0.126*	-0.0741	-0.0911**	-0.0755
	(0.0370)	(0.0567)	(0.0694)	(0.0537)	(0.0379)	(0.0539)
$L2 : \Delta P^2$	-0.0204	-0.116**	-0.117	-0.182	-0.0825*	0.0146
	(0.0218)	(0.0506)	(0.0756)	(0.0256)	(0.0425)	(0.0688)
$L3 : \Delta P^2$		-0.0191	-0.0587		-0.0720**	-0.0320
		(0.0456)	(0.0559)		(0.0344)	(0.0537)
$L4 : \Delta P^2$			0.0250			0.0870**
			(0.0495)			(0.0377)
ΔP	0.0897	0.356	0.371*	0.221*	0.558***	0.358**
	(0.148)	(0.264)	(0.197)	(0.131)	(0.141)	(0.150)
$L1 : \Delta P$	0.128	0.212	0.469	0.228	0.244*	0.256
	(0.173)	(0.248)	(0.285)	(0.159)	(0.138)	(0.182)
$L2 : \Delta P$	0.0386	0.314	0.409	0.0071	0.205	-0.0460
	(0.097)	(0.221)	(0.310)	(0.065)	(0.135)	(0.200)
$L3 : \Delta P$		-0.0769	0.157		0.130	0.0190
		(0.1893)	(0.2306)		(0.1274)	(0.2068)
$L4 : \Delta P$			-0.146			-0.270*
			(0.2023)			(0.1517)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.266	0.341	0.499	0.297	0.410	0.583
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Columns (1) and (3) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. Standard errors clustered at the country level are in parentheses. ***p <0.01, **p <0.05, *p <0.10

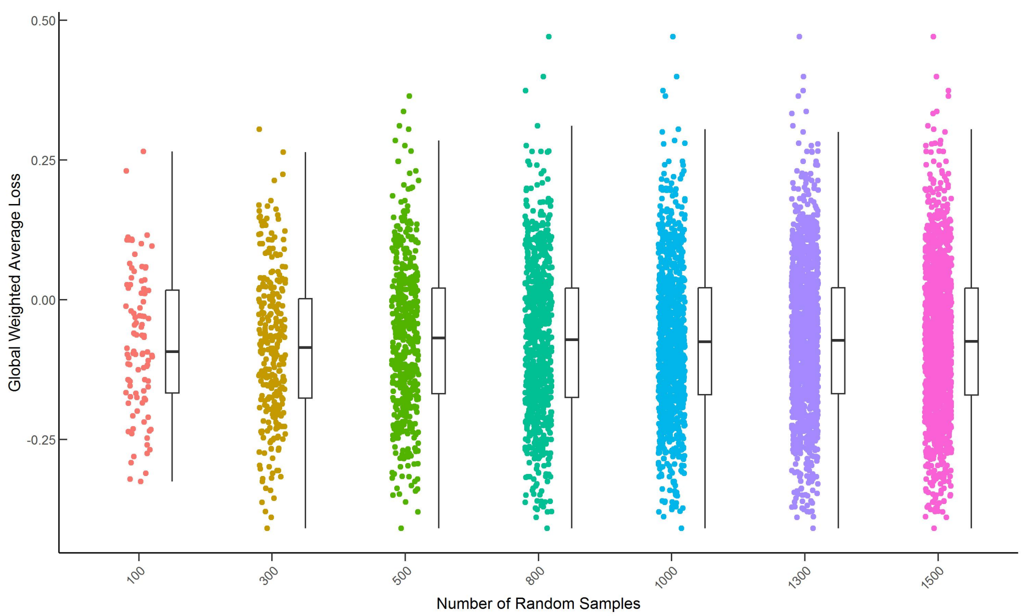

FIGURE A2. BOOTSTRAPPED ESTIMATES WITH DIFFERENT SAMPLES

Table A4—Extended long difference results between poor and rich regions

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
$\Delta T^2 \times poor$	-0.00859***	-0.00562*	-0.00648**	-0.00155	-0.00141	-0.00558*
	(0.0029)	(0.0034)	(0.0026)	(0.0015)	(0.0021)	(0.0017)
$L1 : \Delta T^2 \times poor$	-0.0100***	-0.00715***	-0.00290	-0.00536***	-0.00356**	-0.00117
	(0.0038)	(0.0023)	(0.0027)	(0.0020)	(0.0017)	(0.0030)
$L2 : \Delta T^2 \times poor$	-0.00373	-0.00944***	-0.00649*	-0.000768	-0.00210	-0.00692
	(0.0029)	(0.0024)	(0.0033)	(0.0025)	(0.0028)	(0.0043)
$L3 : \Delta T^2 \times poor$		-0.00119	-0.00542*		0.0000182	-0.00289
		(0.0031)	(0.0031)		(0.0031)	(0.0031)
$L4 : \Delta T^2 \times poor$			-0.00183			-0.00696*
			(0.0025)			(0.0038)
$\Delta T \times poor$	0.345***	0.165	0.242**	-0.0325	-0.102	0.0900
	(0.1322)	(0.1347)	(0.0935)	(0.1330)	(0.1248)	(0.1387)
$L1 : \Delta T \times poor$	0.341**	0.145**	-0.00132	0.156**	0.103	0.0000209
	(0.1364)	(0.0666)	(0.0741)	(0.0733)	(0.0708)	(0.1309)
$L2 : \Delta T \times poor$	0.150	0.326***	0.261***	0.00344	0.123	0.328**
	(0.1010)	(0.0709)	(0.0979)	(0.0787)	(0.0900)	(0.1527)
$L3 : \Delta T \times poor$		0.0333	0.267***		0.110	0.333***
		(0.1120)	(0.0770)		(0.1295)	(0.1178)
$L4 : \Delta T \times poor$			0.128			0.324**
			(0.0793)			(0.1401)
$\Delta T^2 \times rich$	-0.00569**	-0.00357	-0.00474	0.00225	0.000917	0.00291
	(0.0022)	(0.0024)	(0.0037)	(0.0015)	(0.0023)	(0.0021)
$L1 : \Delta T^2 \times rich$	-0.00291*	-0.00154	-0.000145	-0.00199**	0.000126	0.00174
	(0.0018)	(0.0025)	(0.0033)	(0.0010)	(0.0014)	(0.0024)
$L2 : \Delta T^2 \times rich$	-0.00183	-0.00346	0.00159	0.00206	-0.00183	0.00922***
	(0.0021)	(0.0025)	(0.0034)	(0.0020)	(0.0035)	(0.0032)
$L3 : \Delta T^2 \times rich$		-0.0000867	-0.00341		0.00129	-0.00172
		(0.0022)	(0.0034)		(0.0017)	(0.0023)
$L4 : \Delta T^2 \times rich$			0.00235			0.00551***
			(0.0023)			(0.0018)
$\Delta T \times rich$	0.181***	0.0902	0.137	-0.0504	-0.0159	-0.0345
	(0.0608)	(0.0737)	(0.1127)	(0.0541)	(0.0772)	(0.0688)
$L1 : \Delta T \times rich$	0.129*	0.0482	-0.0139	0.0739**	-0.0380	-0.0606
	(0.0689)	(0.0693)	(0.0891)	(0.0361)	(0.0476)	(0.0669)
$L2 : \Delta T \times rich$	0.0500	0.117	0.0232	-0.0882*	0.0236	-0.245***
	(0.0635)	(0.0902)	(0.1124)	(0.0484)	(0.0698)	(0.0590)
$L3 : \Delta T \times rich$		-0.00188	0.143		-0.0788*	0.0281
		(0.0652)	(0.1331)		(0.0468)	(0.0687)
$L4 : \Delta T \times rich$			-0.0133			-0.111**
			(0.0852)			(0.0520)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.276	0.352	0.511	0.319	0.429	0.612
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Standard errors clustered at the country level are in parentheses. Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. ***p <0.01, **p <0.05, *p <0.10

TABLE A5—EXTENDED LONG DIFFERENCE RESULTS BETWEEN POOR AND RICH REGIONS WITH ALL VARIABLES(CONTINUED)

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
$\Delta P^2 \times poor$	-0.0671	-0.0625	0.00244	-0.143**	-0.169***	-0.146**
	(0.0709)	(0.0664)	(0.0595)	(0.0650)	(0.0588)	(0.0730)
$L1: \Delta P^2 \times poor$	-0.0350	-0.0504	-0.0745	-0.0187	-0.0669	-0.0840
	(0.0344)	(0.0759)	(0.1150)	(0.0588)	(0.0565)	(0.0899)
$L2: \Delta P^2 \times poor$	-0.0438	-0.0655	0.0466	-0.0781	-0.0703	-0.0332
	(0.0510)	(0.0640)	(0.1309)	(0.0455)	(0.0471)	(0.0852)
$L3: \Delta P^2 \times poor$		-0.0195	-0.0460		-0.0653	-0.0663
		(0.0605)	(0.0873)		(0.0530)	(0.0893)
$L4: \Delta P^2 \times poor$			0.0413			0.0194
			(0.0667)			(0.0775)
$\Delta P \times poor$	0.271	0.153	-0.0256	0.493*	0.739***	0.557*
	(0.3011)	(0.2991)	(0.2569)	(0.2763)	(0.2685)	(0.2917)
$L1: \Delta P \times poor$	0.0435	0.00916	0.171	0.0512	0.220	0.458
	(0.1582)	(0.2973)	(0.4054)	(0.2385)	(0.2313)	(0.4006)
$L2: \Delta P \times poor$	0.0329	0.0114	-0.350	0.145	0.187	0.111
	(0.2396)	(0.2735)	(0.4568)	(0.2365)	(0.2922)	(0.4492)
$L3: \Delta P \times poor$		-0.126	0.0172		0.173	0.307
		(0.2468)	(0.3312)		(0.2245)	(0.4295)
$L4: \Delta P \times poor$			-0.233			-0.0122
			(0.2572)			(0.2984)
$\Delta P^2 \times rich$	-0.0643	-0.148*	-0.171***	-0.218***	-0.150**	-0.0761
	(0.0874)	(0.0845)	(0.0647)	(0.0556)	(0.0698)	(0.0554)
$L1: \Delta P^2 \times rich$	-0.0291	-0.0926	-0.134*	-0.0926*	-0.0996**	-0.108*
	(0.0568)	(0.0687)	(0.0736)	(0.0519)	(0.0481)	(0.0605)
$L2: \Delta P^2 \times rich$	-0.0897	-0.164**	-0.198**	-0.199***	-0.105	0.0355
	(0.0695)	(0.0793)	(0.0898)	(0.0521)	(0.0756)	(0.0642)
$L3: \Delta P^2 \times rich$		-0.0155	-0.0504		-0.0538	-0.0411
		(0.0629)	(0.0683)		(0.0328)	(0.0502)
$L4: \Delta P^2 \times rich$			0.0376			0.133***
			(0.0741)			(0.0372)
$\Delta P \times rich$	0.166	0.485	0.573*	0.710***	0.558*	0.306
	(0.3802)	(0.4077)	(0.2968)	(0.2509)	(0.2907)	(0.2608)
$L1: \Delta P \times rich$	0.146	0.323	0.639*	0.256	0.275	0.276
	(0.2772)	(0.3611)	(0.3795)	(0.1777)	(0.1874)	(0.2001)
$L2: \Delta P \times rich$	0.350	0.634*	0.872**	0.609***	0.300	-0.0595
	(0.3180)	(0.3686)	(0.4091)	(0.2050)	(0.2179)	(0.2323)
$L3: \Delta P \times rich$		-0.0152	0.287		0.0834	0.0110
		(0.2900)	(0.3325)		(0.1150)	(0.1664)
$L4: \Delta P \times rich$			-0.127			-0.405**
			(0.2965)			(0.1921)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.276	0.352	0.511	0.319	0.429	0.612
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Standard errors clustered at the country level are in parentheses. Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. ***p <0.01, **p <0.05, *p <0.10

Table A6—Effects of Climate Levels and Variations on Output Growth in Rich and Poor Regions

	(1) No-lag	(2) One-lag	(3) Two-lag	(4) No-lag	(5) One-lag	(6) Two-lag
Sum of coeff. of ΔT^2 in poor	-0.0239***	-0.0248***	-0.0315***	-0.0134***	-0.00781	-0.0222
	(0.00563)	(0.00753)	(0.00973)	(0.00501)	(0.00656)	(0.0142)
Sum of coeff. of ΔT in poor	0.825***	0.707**	1.09***	-0.0572	0.103	0.84
	(0.197)	(0.289)	(0.365)	(0.234)	(0.303)	(0.581)
Sum of coeff. of ΔT^2 in rich	-0.0105**	-0.0103	-0.00177	0.000464	-0.00358	0.0111
	(0.00424)	(0.00798)	(0.0158)	(0.0021)	(0.00644)	(0.00739)
Sum of coeff. of ΔT in rich	0.327	0.067	-0.225	-0.0395	-0.286*	-0.692***
	(0.211)	(0.245)	(0.474)	(0.118)	(0.172)	(0.238)
Sum of coeff. of ΔP^2 in poor	-0.120	-0.283	-0.403	-0.118	-0.282	-0.485
	(0.129)	(0.295)	(0.475)	(0.168)	(0.187)	(0.347)
Sum of coeff. of ΔP in poor	0.379	0.772	1.70	0.349	1.14	2.30
	(0.587)	(1.09)	(1.96)	(0.578)	(0.463)	(1.15)
Sum of coeff. of ΔP^2 in rich	-0.158	-0.417	-0.443	-0.411***	-0.235*	-0.0646
	(0.22)	(0.261)	(0.404)	(0.112)	(0.137)	(0.158)
Sum of coeff. of ΔP in rich	0.536	1.93	2.87	0.881	-0.318	-0.354
	(1.02)	(1.41)	(2.1)	(0.602)	(0.639)	(0.90)
Sum of coeff. of ΔAST^2 in poor	0.0134	0.0437**	0.0422	-0.0328	0.00529	0.0245
	(0.0125)	(0.0171)	(0.0313)	(0.0137)	(0.0336)	(0.0518)
Sum of coeff. of ΔAST in poor	0.0389	0.0408	-0.00905	0.138***	0.0943*	0.0187
	(0.0309)	(0.0467)	(0.092)	(0.043)	(0.0527)	(0.174)
Sum of coeff. of ΔAST^2 in rich	0.00354	0.0372	0.0486	-0.0204	-0.00427	-0.00892
	(0.0271)	(0.035)	(0.0498)	(0.0229)	(0.0334)	(0.0446)
Sum of coeff. of ΔAST in rich	0.0128	0.0852	0.159	0.0167	0.117	0.165
	(0.0747)	(0.101)	(0.158)	(0.0467)	(0.0714)	(0.128)
Sum of coeff. of ΔASP^2 in poor	0.0621***	0.0457*	0.0173	0.0397	0.0467	-0.0549
	(0.02)	(0.0259)	(0.0531)	(0.0328)	(0.0512)	(0.0701)
Sum of coeff. of ΔASP in poor	-0.00877	-0.0503	-0.143	0.0476	0.0308	-0.0265
	(0.0603)	(0.109)	(0.143)	(0.0638)	(0.0907)	(0.142)
Sum of coeff. of ΔASP^2 in rich	0.0112	-0.00515	-0.0832	0.0221	-0.00821	-0.0229
	(0.0425)	(0.0616)	(0.0827)	(0.0228)	(0.041)	(0.0637)
Sum of coeff. of ΔASP in rich	-0.000254	-0.0997	-0.106	0.0784	0.229***	0.158*
	(0.0744)	(0.107)	(0.16)	(0.0684)	(0.0829)	(0.0916)
Obs.	8330	6664	4998	8330	6664	4998
R^2	0.295	0.381	0.545	0.347	0.453	0.640
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Weight	Region	Region	Region	Pop.	Pop.	Pop.

Note: Standard errors clustered at the country level are in parentheses. Columns (1) and (4) are estimated based on constrained linear regression, with the constraints $\rho_0 + \rho_2 = \rho_1$ and $\sigma_0 + \sigma_2 = \sigma_1$. ***p <0.01, **p <0.05, *p <0.10